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# Analysing, visualising and supporting collaborative learning using interactive tabletops

Roberto Martinez Maldonado

A thesis submitted in fulfilment of the requirements  
for the degree of Doctor of Philosophy in  
the School of Information Technologies at  
The University of Sydney, Australia.



Computer Human Adapted Interaction Research Group  
School of Information Technologies  
Faculty of Engineering and Information Technologies  
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# Abstract

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Collaboration in learning contexts can promote students to externalise their personal perspectives in order to reach shared understanding and integrate individual with group knowledge. It has been recognised that collaborative learning can enhance the capacity of thinking by triggering particular learning mechanisms that cannot be activated by individual learning. Additionally, collaboration skills are often considered to be key conditions for value generation beyond the classroom, into the workplace. However, students working together do not spontaneously collaborate, even if they are supported by computer systems. Thus, teachers have a central role in providing feedback and helping students to learn to collaborate effectively. However, in classroom environments, even in small group activities, it is challenging for teachers to provide students the attention that they may require and be aware of the process followed by each group. Teachers need tools that can provide them with coarse-grained feedback that allows them to monitor what is happening in their classes.

Multi-user pervasive shared devices have great potential for addressing this situation. In particular, interactive tabletops provide an enriched space where students can communicate face-to-face with each other and, at the same time, interact with a large work area that has access to digital content allowing the creation of persistent artefacts. Tabletops provide an environment in which students can decide whether they work in parallel, or together as a group. A slightly hidden potential of interactive tabletops, that this thesis explores, is that they can open new opportunities for capturing learner's digital traces of activity. These data can be analysed through a variety of techniques, from simple statistics or visualisations that describe general aspects of student's activity, to data mining and user modelling techniques that can be used to find patterns or train models of interaction. Furthermore, the analysis of such data can provide means to help teachers and researchers inspect the process followed by students and recognise patterns of group behaviour.

We identify a number of open issues that are currently present in each of the three fields involved in this thesis: tabletops in education from a Computer Supported Collaborative Learning (CSCL) perspective; Educational Data Mining and analytics (EDM); and research on interactive tabletop applications from a Human-Computer Interaction perspective (HCI). The intersection of these fields raises a challenging question: *How can interaction data be automatically exploited to inform teachers and enhance their awareness of student's collaborative activity using interactive tabletops?* One of the first challenges is in forming a basis for the design of the tabletop environment and its associated collaborative interfaces, so that they can capture the required collaboration data. This must be done in a manner that makes it possible to do downstream analysis of the data and present it in a form that facilitates understanding of the collaborative learning processes.

The key contribution of this thesis is a novel approach to design, implement and evaluate the conceptual and technological infrastructure that captures student's activity at interactive tabletops and analyses these data through Interaction Data Analytics techniques to provide support to teachers by enhancing their awareness of student's collaboration. To achieve the above, this thesis presents a series of carefully designed user studies to understand how to capture, analyse and distil indicators of collaborative learning. We perform this in three steps: the exploration of the feasibility of the approach, the construction of a novel solution and the execution of the conceptual proposal, both under controlled conditions and in the wild. A total of eight datasets were analysed for the studies that are described in this thesis.

We begin with foundational exploratory studies on collocated environments that enable us to understand the requirements that are needed to analyse and discover patterns of face-to-face interaction. The results of that study, in addition to the foundations of existing literature, are used to inform a set of design requirements for building an effective tabletop environment that can



automatically and unobtrusively capture rich student's data. A subordinated contribution of the thesis is the design and implementation of this system. The system extends an ordinary interactive tabletop to differentiate which learner is touching what and which student is speaking in a non-intrusive manner. The next contribution is the design and validation of a set of visualisations of student's interactions that can be shown to researchers, teachers or students, to foster awareness and reflection. These visualisations also serve as building blocks to create a teacher's dashboard that can show collaboration indicators of multiple groups, to be used either in *real-time* or for post-hoc analysis.

From the data analysis perspective, this thesis also contributes to the deep exploration of collaborative interactions by integrating data coming from multiple sources (touch interaction with the shared device, speech differentiation, characteristics of the artefacts and measures of learning). A series of studies in the lab offers the opportunity to analyse a large amount of detailed learner's data. Such analysis includes the application of data mining and statistical techniques to discover meaningful patterns that can help differentiate high from low achieving groups.

Finally, the contribution that is most strongly associated with the real practice is the implementation of a solution for an authentic classroom using multiple interactive tabletops. This classroom environment offers a number of functionalities for the teacher to orchestrate the script of the classroom session and look at live-visualisations of the on-task progress of each small group. This approach can help teachers decide which group to attend next. The analysis also includes the discovery of trends in students interactions that can make visible aspects of collaborative work that may not be easily seen without the use of such technology.

Our work pioneered in a number of areas including the application of data mining techniques to study collaboration at the tabletop, a plug-in solution to add user-identification to a regular tabletop using a depth sensor and the first multi-tabletop classroom used to run authentic collaborative activities associated with the curricula.

In summary, while the mechanisms, interfaces and studies presented in this thesis were mostly explored in the context of interactive tabletops, the findings are likely to be relevant to other forms of groupware and learning scenarios that can be implemented in real classrooms. Through the mechanisms, the studies conducted and our conceptual framework this thesis provides an important research foundation for the ways in which interactive tabletops, along with data mining and visualisation techniques, can be used to provide support to improve teacher's understanding about student's collaboration and learning in small groups.

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# Preface and Notes

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## Publications during candidature

### Journal article

- R. Martinez-Maldonado**, Y. Dimitriadis, A. Martinez-Monés, J. Kay, and K. Yacef. Capturing and analyzing verbal and physical collaborative learning interactions at an enriched interactive tabletop. *International Journal of Computer-Supported Collaborative Learning*, 8(4), 455-485 (2013b).

### Conference papers

#### 2013

- R. Martinez-Maldonado**, J. Kay, K. Yacef, M. Edbauer and Y. Dimitriadis. MTClassroom and MTDashboard: Supporting Analysis of Teacher Attention in an Orchestrated Multi-tabletop Classroom In *International Conference on Computer-Supported Collaborative Learning, CSCL 2013*, pages 119-128, (2013a).
- R. Martinez-Maldonado**, J. Kay and K. Yacef. An automatic approach for mining patterns of collaboration around an interactive tabletop. In *International Conference on Artificial Intelligence in Education, AIED 2013*, pages 101-110, (2013c).
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- R. Martinez-Maldonado**, J. Kay, K. Yacef, M. Edbauer and Y. Dimitriadis. Orchestrating a Multi-tabletop Classroom: from design to enactment and reflection. In *International Conference on Interactive Tabletops and Surfaces, ITS 2012*, pages 119-128, (2012d).
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- R. Martinez-Maldonado**, J. Kay, K. Yacef, and J. Wallace. Modelling symmetry of activity as an indicator of collocated group collaboration. In *19th International Conference on User Modeling, Adaptation and Personalization, UMAP 2011*, pages 196-204, (2011c).

**R. Martinez-Maldonado**, J. Wallace, J. Kay, and K. Yacef. Modelling and identifying collaborative situations in a collocated multi-display groupware setting. In *International Conference on Artificial Intelligence in Education, AIED 2011*, pages 196-204, (2011e).

2010

**R. Martinez-Maldonado**, J. Kay, and K. Yacef. Collaborative concept mapping at the tabletop. In *ACM International Conference on Interactive Tabletops and Surfaces, ITS 2010*, pages 207-210, (2010a).

#### Workshop papers

A. Clayphan, **R. Martinez-Maldonado**, and J. Kay. Designing OLMs for Reflection about Group Brainstorming at Interactive Tabletops. In Workshop on Intelligent Support for Learning in Groups - held at International Conference on Artificial Intelligence in Education (AIED 2013), Memphis, USA. (2013c).

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C. Ackad, A. Clayphan, **R. Martinez-Maldonado**, and J. Kay. Seamless and continuous user identification for interactive tabletops using personal device handshaking and body tracking. In *Work-In-Progress CHI '2012*, Austin, USA, pages 1775-1780, (2012).

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#### Media coverage:

The Sydney Morning Herald. The classroom, but not as we know it: technology to revolutionise schools. July 16, 2012

#### Other papers:

##### Edited proceedings:

**R. Martinez-Maldonado**, J. Slotta, P. Dillenbourg, A. Clayphan, M. Tissenbaum, B. Schwendimann and C. Ackad. Digital Ecosystems for Collaborative Learning: Embedding Personal and Collaborative Devices to Support Classrooms of the Future, - held at International Conference on Learning Sciences (ICLS 2012), Sydney, Australia. 2012.

##### Publications in Spanish:

M. Moreno and **R. Martinez-Maldonado**. Modelo clasificador para predecir el desempeño escolar terminal de un estudiante. In Conferencia Iberoamericana en Sistemas, Cibernética e Informática (CISCI 2011), pages 47-51, 2011.

D. Moreno, D. Cano, C. Hau, **R. Martinez-Maldonado**. and M. Moreno. Integración de un Tabletop utilizando Kinect como Herramienta Educativa. In Congreso Nacional de Ingeniería Eléctrica y Electrónica del Mayab (CONIEEM2011), 2011.

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**R. Martinez-Maldonado**. Mining the collaborative learning process at the tabletop to offer adapted support. In *ACM International Conference on Interactive Tabletops and Surfaces, ITS 2011*, 2011.

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M. Evans, J. Rick, M. Horn, C. Shen, E. Mercier, J. McNaughton, S. Higgins, M. Tissenbaum, M. Lui, J. Slotta, A. Clayphan, **R. Martinez-Maldonado**. Interactive Surfaces and Spaces: A Learning Sciences Agenda. In *International Conference of the Learning Sciences: The Future of learning, ICLS 2012*, pages 78-85, 2012.

Peer-reviewed Posters:

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## Sources & Original Work

Original material of my own from the above publications has been included in this thesis, with a citation to the appropriate publication appearing at the beginning of each chapter. Other external sources are cited, with the bibliography appearing at the end of the thesis. The background chapter (Chapter 2) contains figures from external sources, with permission from their authors. In such a case, the reference to the source of the figure is indicated in the caption.

## Use of Work by Others

Two out of the eight student's datasets that are analysed in this thesis were collected through studies conducted by fellow researchers. The first of them was collected by Wallace et al. (2009) from an interconnected multi-display collaborative environment that allows students to work face-to-face. The second dataset was collected by Kharrufa et al. (2010) and consists of the differentiated student's logged actions at a pen-based collaborative learning tabletop application. However, the pre-processing and analysis of these data are part of the original contributions of this thesis.

## Human Ethics

Studies presented in this thesis were conducted under human ethics protocol number 13061, entitled "*Data Mining on the process of concept mapping at the tabletop*". It was approved by The University of Sydney Human Research Ethics Committee on 4th July, 2010. The most updated Participant information statements and consent forms can be requested by email.<sup>1</sup>

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<sup>1</sup> Email addresses: roberto@it.usyd.edu.au, kalina@it.usyd.edu.au or judy@it.usyd.edu.au

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# Chapter 1: Introduction

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*"New technology is common; new thinking is rare"*

-Sir Peter Blake

**Summary:** This chapter describes the research context of the thesis, the identified learning problem and the methodology followed to address it. This thesis builds on the intersection of three fields: Human-Computer Interaction (HCI), Computer-Supported Collaborative Learning (CSCL) and Educational Data Mining (EDM). The thesis proposes a conceptual framework as a result of a deep exploration of different ways that student's data can be used to help understand different aspects of collaboration using interactive tabletops. The thesis shows how student's data can be exploited to enhance teacher's awareness through a series of instantiations of this framework. This chapter outlines the goals, contributions, evaluation methods and the general structure of the rest of the thesis.

## 1.1. Context and Motivation

The many benefits of collaboration on learning and knowledge sharing, especially when it is mediated by technology, are well documented in the Computer-Supported Collaborative Learning (CSCL) research area. Collaboration can promote learners to externalise their personal perspectives in order to reach shared understanding and integrate individual with group knowledge (Scardamalia and Bereiter, 1991; Stahl, 2006). *Collaborative learning* can enhance the thinking capacity by triggering particular learning mechanisms that cannot be activated by individual learning (Dillenbourg, 1998). It can also lead to improved critical thinking, reduced task workload, increased retention, and a more positive attitude towards the subject matter (Berland and Reiser, 2009; Felder and Brent, 1994; Johnson and Johnson, 1986).

Collaboration is not a single mechanism; most of the time it requires all group members to engage in a coordinated effort to provide a joint solution to a problem (Roschelle and Teasley, 1995). It also demands the development of a number of skills. Therefore teachers have a central role in fostering enhanced performance by monitoring the collaborative process, providing feedback and helping students to be more aware of their group dynamics (Dillenbourg et al., 2011; Kirschner, 2001; Slavin, 1983; Webb, 2009). The development of skills for effective collaboration is crucial, not only in educational settings, but also to meet real-world challenges (Scheuer et al., 2010). In particular, *face-to-face* (f2f) collaboration provides benefits that are not easy to find in other forms of group work (Johnson et al., 2000). These include a natural channel for continuous communication, exchange of non-verbal cues, and an increased productivity in completing tasks (Olson et al., 2002).

Without adequate feedback, however, group members do not always naturally collaborate to complete their joint task (Dillenbourg, 1998), even if they are supported by a computer system (Kreijns et al., 2003). Indeed, they may find that it requires too much time and additional effort. This means that in collaborative learning environments, it is important for the teacher to be aware of student's collaboration in order to provide support (O'Donnell, 2006). In real classrooms, teachers have to manage their limited resources and time to attend to students, each with different learning styles, strengths and needs. Even during small group activities, it is challenging for teachers to provide, even to each group, the one-on-one attention that they may require (Zhang et al., 2004). Teachers may try to identify the groups that are collaborating more effectively, to allow them to work more independently so that the teacher can focus on groups that need attention. As a result, teachers generally cannot be aware of the process that some groups followed (Race, 2001). At the end of the class, the teacher may not be able to know what happened within certain groups and usually they have to assess their performance based only on the final product of the activity. Nevertheless, the final product provides very limited information about the collaborative process, individual contributions or previous states of the solution that may have been of good quality.

Pervasive technologies can be used to address this problem. Research on Human-Computer Interaction (HCI) has recently shown promise for the development of emerging pervasive shared devices, such as *interactive tabletops*, for supporting students to collaborate and for their teachers to monitor face-to-face group work (Kharrufa, 2010). The affordances of interactive tabletops include the provision of a work space that offers equal opportunities of participation for each learner, repeatability when working with virtual content, and digital resources that students can use to build a solution (Piper and Hollan, 2009). Tabletops provide an environment in which students can decide whether they work in parallel or as a group entity. They also open up new opportunities for capturing learner's *digital footprints*. This can offer teachers and researchers the possibility to gain awareness of the process followed by the students, helping those teachers or researchers to identify behaviour patterns and understand how learners collaborate. Therefore, interactive tabletops can offer a new way to explore the body of research of CSCL to help teachers support student's face-to-face collaboration.

The third area of research that can provide with methods to exploit the rich contextual data that can be captured from the interactions of students with the tabletops and with their peers is the emerging field of Educational Data Mining (EDM) (Baker and Yacef, 2009). Data mining, artificial intelligence or even simple statistical approaches can be used to find patterns of student's activity associated with higher level strategies or behaviours. These patterns may help produce indicators of effective collaboration or less desired learning outcomes. However, most of the proposals for automatic analysis in this research area, as in related fields, such as Learning Analytics (Siemens and Baker, 2012) and the analysis of computer-supported collaboration (Soller et al., 2005), are mostly intended for networked remote collaboration settings. In most of these systems it is possible to record student's interactions that are mediated by the technology, but all their face-to-face communication or interactions through other mediums are usually neglected.

When applied to face-to-face settings, computer-supported collaboration analysis is mostly based on video and audio recordings (Jeong and Hmelo-Silver, 2010), and oriented to researchers, whose focus is on the deep and detailed insights enabled by these streams of data. By contrast, teachers need tools that provide them coarse-grained key information that allows them to monitor what is happening in their classes (Dillenbourg et al., 2011). However, collocated collaboration is strongly based on verbal interaction and therefore not mediated by the technology. The integration of this verbal activity with the data stored by learning systems, such as activity logs, learning outcomes and student's artefacts, requires technological infrastructures that are able to capture data from multiple sources and the analysis methods that exploit this integration.

The intersection of the three fields, CSCL, HCI and EDM/data analytics, in this context, raises a challenging question: **How can interaction data be automatically exploited to inform teachers and enhance their awareness of student's collaborative activity using interactive tabletops?** In order to address this, three sub-problems arise from the previous question:

1. *What information is required to analyse collaborative learning in existing face-to-face interaction datasets?* Addressing this question includes the exploration of existing face-to-face settings to investigate if it is possible to produce indicators of group work that can provide relevant information of collaboration and learning. Validating the feasibility of extracting interesting patterns from existing settings serves as a foundation to define the characteristics of the targeted learning situation and a number of guidelines regarding the collaboration data that should be captured.
2. *What are the design features of a system that can unobtrusively capture and show interaction data?* This is particularly important for face-to-face settings in which the communication between peers is rich, wide and can occur through different channels that the computer cannot (and perhaps should not) mediate (e.g. speech, gaze, body language or assenting). A first challenge is to define what interaction data should be captured and what data can be captured using the currently available technology while, at the same time, students interact naturally. A second challenge is to implement a solution for capturing face-to-face interaction data unobtrusively to avoid causing changes in student's collaboration influenced by the capturing system.
3. *How can interaction data be analysed and distilled to enhance teacher's awareness of group collaboration and the progress in their task?* The third issue is to find ways to produce key patterns of interaction that can be discovered from student's data. A follow up issue is to find the effective ways in which group indicators can be shown to the teacher, in the form of visualisations or succinct information, to enhance their awareness during the classroom sessions or for after class reflection.

## 1.2. Thesis Statement

This thesis aims to address the three questions posed above through the following statement that embodies the approach of this thesis for *supporting teacher's awareness of small group's collaboration*.

**To design, implement and evaluate the conceptual and technological infrastructure that can capture student's individual and collaborative activities as they build shared knowledge at an interactive tabletop and analyse these data through Interaction Data Analytics techniques to provide support to teachers by enhancing their awareness of student's collaboration.**

Figure 1-1 (context) lists a set of keywords that can help understand the crossing of the three domains, CSCL, HCI and EDM, in terms of the thesis statement (in particular, and in no order, *interaction data capture, interactive tabletops for learning, interaction data analytics, visualisations and classroom orchestration*).

In order to provide support to teachers, the system should be able to automatically *capture student's interaction* data in a way that it does not interfere with the natural process of collaboration or restrict student's interactions with the technology or their peers. Additionally, explorations of *interactive tabletops for learning* are important to be considered because the multi-touch applications should provide usability and interaction affordances that at least do not produce a negative impact on student's coordination.

In this thesis we will use the concept of *interaction data analytics* to refer to the analysis techniques that can be applied to exploit the rich interaction data that can be captured from a collaborative learning environment. Under this umbrella we include artificial intelligence approaches, data mining algorithms, process mining, statistics and visualisations (EDM and Learning Analytics techniques). A fourth key term that is relevant in this thesis is *classroom orchestration* (Dillenbourg et al., 2011), more specifically the dimensions of teacher's awareness and classroom control (Prieto-Santos, 2012). The metaphoric term, *classroom orchestration*, is used to describe the

role that teachers take as managers and coordinators of the cognitive, pedagogic and technological resources in the classroom, to help students achieve the intended goals of the learning activities (Prieto et al., 2011). The effectiveness of orchestration and the extent to which teachers can respond to the ways students perform the class tasks is critical because it directly impacts these student's activities, and therefore, their learning (Dillenbourg et al., 2011). The use of technology-based tools can improve the teacher's management of the class and enhance their awareness of learner's activity. For the later, *visual representations* can be produced from the interaction data and be shown to teachers so they can quickly make informed decisions during the class and provide more effective feedback to the students. This information may consist of visualisations, numerical summaries or graphs that can provide teachers with meaningful insights on which groups might need attention and which ones can be left to work by themselves at that point in time.

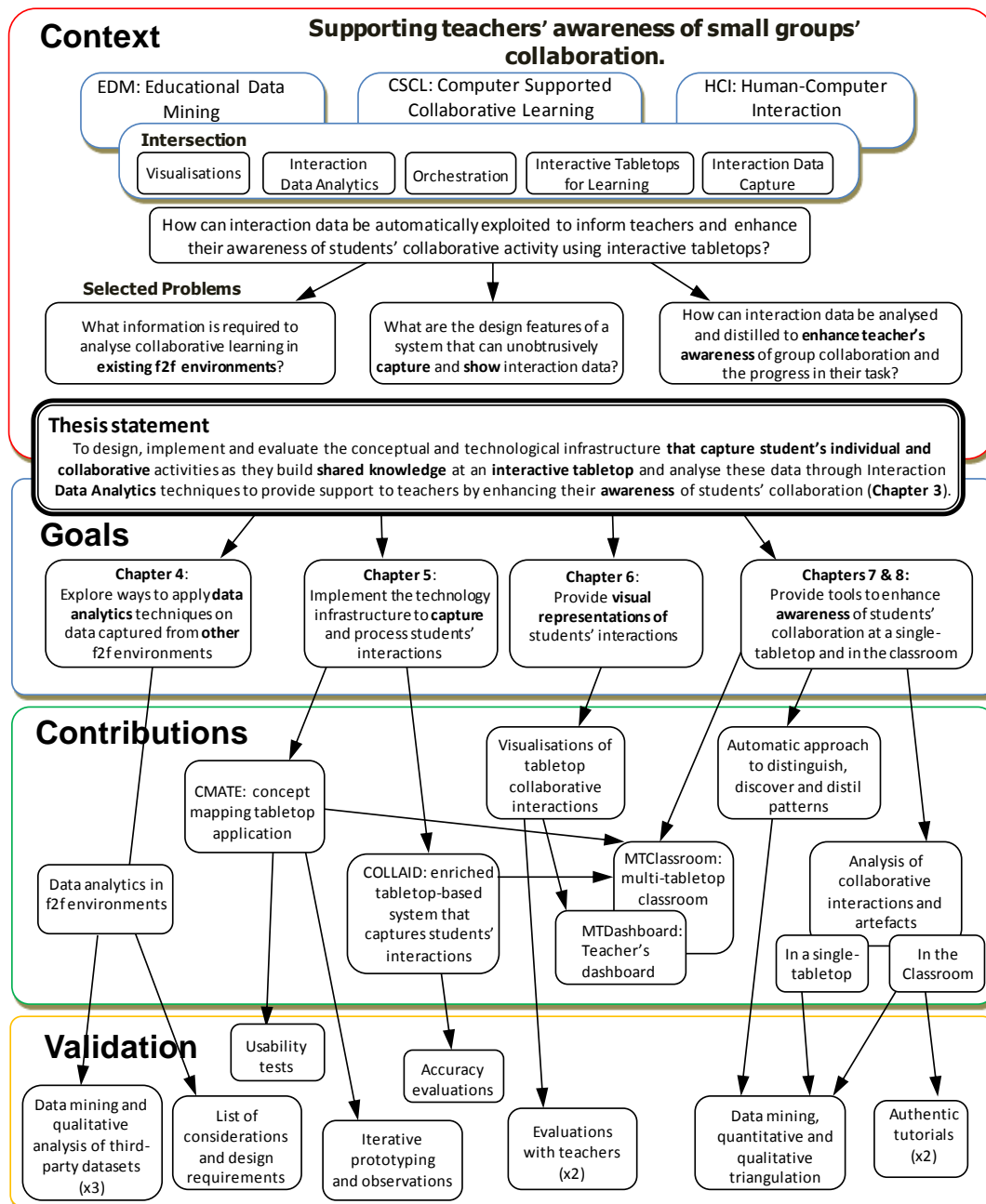


Figure 1-1 Overview of the context, goals, contributions and evaluation of this thesis.

In order to deliver the conceptual and technological elements, this thesis builds on the following principles to design an approach to support a collocated collaborative learning situation.

1. *Automatic*. The approach aims to provide group indicators that require little or no human intervention to be produced. The goal is to enhance teacher's awareness of student's interactions and learning processes that might not be evident for a teacher by looking at a group's final products, but that can be captured by the computer system.
2. *Unobtrusive*. This principle is crucial to keep all the data capture elements decoupled from the learning setting to allow natural face-to-face collaboration. Additionally, the ultimate goal is to provide tools that can be deployed in the classroom and not only under constrained experimental settings.
3. *Authentic deployment*. The third element defines the learning situation this thesis aims to support. This is a real environment in which students have a clear learning goal that is connected to the regular curricula of the subject matter they study.
4. *In-time support*. Finally, the approach aims to provide useful awareness indicators during the classroom sessions in the time available. It is also important to deliver additional key information for post-classroom analysis, assessment or activity re-designs.

It is important to state that these four principles define the ultimate and driving goal for the target computer-mediated collaborative situation. However, the studies described in this thesis are based on these principles, each building towards the goal.

## 1.3. Thesis Goals

Having described the research context and stated the thesis statement, we have formulated the main goals of the thesis (see Figure 1-1, Goals):

1. *Explore ways to apply data analytics techniques on data captured from other face-to-face environments*. There is very little previous work on developing automated tools for analysing student's face-to-face collaboration (Jeong and Hmelo-Silver, 2010; Martinez-Maldonado et al., 2011e). However, there is substantial research work on analysing student collaboration mediated by networked systems (Soller et al., 2005), and that work can serve as a foundation to explore techniques that might also be suitable for collocated environments. This goal addresses our question: *What information is required to analyse collaborative learning in existing face-to-face interaction datasets?* For this, we explored two face-to-face learning settings: i) a multi-display environment in which students were asked to solve an optimisation problem, and ii) a pen-based tabletop tool called *Digital Mysteries* that allowed school students to gather information from virtual content presented by the application in order to produce an answer to a decision-making task. The aim of this goal was to investigate whether it is possible to find interesting interaction patterns from face-to-face activity logs that can be associated with collaborative behaviours. The outcome is to demonstrate the feasibility of automated analysis in face-to-face settings and outline the conditions and type of data that should be captured for analysis of collaborative interactions. This exploration is mainly described in Chapter 4 and in the following peer-reviewed papers (Martinez-Maldonado et al., 2011c; Martinez-Maldonado et al., 2011e; Martinez-Maldonado et al., 2011f).
2. *Implement the technology infrastructure to capture and process student's interactions*. This goal addresses the first part of our second question: *What are the design features of a system that can unobtrusively capture interaction data?* Based on the outcomes of the previous goal we aimed to design the environment that provides the opportunity for students to decide how to collaborate and at the same time the system can capture the digital footprints of student's activity. To achieve this, we combined face-to-face collaborative learning at an interactive tabletop with a tool that has the potential to foster student's meaningful learning: *concept mapping*. This is a well-established learning tool that can be applied in a number of domains and it is backed up by a strong community of research and practice (Cañas and Novak, 2008). We designed and built i) CMATE, a tabletop-based concept mapping application for



collaborative concept mapping (Martinez-Maldonado et al., 2010a); and ii) COLLAID, a pervasive system that can automatically and unobtrusively capture student's verbal and touch interactions at a tabletop (Martinez-Maldonado et al., 2011b). These systems are described in Chapter 5 and in the following peer-reviewed papers (Martinez-Maldonado et al., 2011a; Martinez-Maldonado et al., 2012b; Martinez-Maldonado et al., 2011b; Martinez-Maldonado et al., 2010a).

3. *Provide visual representations of student's interactions.* It is challenging to define ways to present the information about group collaboration in a manner that is readily understood and useful for educators. This goal addresses the second half of our second question: *What are the design features of a system that can **show** interaction data?* For this reason we designed a large set of visual representations of quantitative indicators of group work and evaluated the impact of showing these to the teacher to enhance their awareness of what happened during the process of group knowledge construction (Martinez-Maldonado et al., 2011d). We further designed and implemented a dashboard to explore the nature of information that the teacher wants to see in-class or after the classroom sessions (Martinez-Maldonado et al., 2012f). We finally validated the usage and impact of a teacher's dashboard in an authentic classroom (Martinez-Maldonado et al., 2013a). The visualisations and dashboards are described in Chapter 6 and also in Chapter 8. Results of the research associated with this goal were published in the following papers (Martinez-Maldonado et al., 2013a; Martinez-Maldonado et al., 2011d; Martinez-Maldonado et al., 2012f).

4. *Provide tools to enhance awareness of student's collaboration at a single-tabletop and the classroom.* This goal addresses our third question: *How can interaction data be analysed and distilled to enhance teacher's awareness of group collaboration and the progress in their task?* This goal calls for the integration of our capturing system, our collaborative learning environment, and the analysis and visualisation tools in order to i) design and implement a *conceptual framework* for capturing and integrating verbal and physical interactions around enhanced interactive tabletops; ii) produce an approach to extract frequent patterns from these traces of activity; and iii) validate the effectiveness of the results to produce insights about collaborative work to be shown to the teacher. We conducted two main sets of studies to enhance awareness about student's collaboration at a single-tabletop in a controlled environment and in the wild (the classroom). In the first case, we created an environment able to record rich contextual information from groups of three students providing a solution to a posed question. Secondly, we developed a multi-tabletop classroom that can be orchestrated by a teacher and, at the same time, can capture student's interactions to produce live-indicators of collaboration. The conceptual framework of this thesis is detailed in Chapter 3. Studies carried out under controlled conditions are described in Chapter 7. The studies of the multi-tabletop orchestrated classroom are presented in Chapter 8. Results of the research associated with this goal were published in the following peer-reviewed papers: in single-tabletop setting (Martinez-Maldonado et al., 2012c, 2013c; Martinez-Maldonado et al., 2012g) and in the classroom (Martinez-Maldonado et al., 2013a; Martinez-Maldonado et al., 2012d; Martinez-Maldonado et al., 2013d).

## 1.4. Thesis Contributions

The main contribution of this thesis is the **design, implementation and evaluation of the conceptual framework and the technological infrastructure for capturing, integrating and analysing traces of student's tabletop activity, to provide support to teachers by enhancing their awareness of student's collaboration.** This is described in Chapter 3. The subsidiary contributions are listed in Figure 1-1 (Contributions) and can be described as follows:

1. *Data analytics in face-to-face settings.* The exploratory studies on collocated environments (Martinez-Maldonado et al., 2012c; Martinez-Maldonado et al., 2011f) that were conducted for this thesis, and more specifically, on interactive tabletops (Martinez-Maldonado et al., 2011f), are part of the first work that applied data mining techniques (classifiers, clustering and

sequence mining), to analyse and discover patterns of interaction from data generated by students collocated around educational groupware.

2. *CMATE: a concept mapping tabletop application.* We built CMATE, a tabletop application that allows learners to draw a concept map that represents their collective understanding about a topic (Martinez-Maldonado et al., 2010a). This application presents novel affordances, including: the integration of artefacts that students produce before working at the tabletop, the provision of personalised content to each student according to the vocabulary they used in previous activities and a multi-layered interface to both maintain the collaboratively created group map as well as one layer per user showing their individual contributions.

3. *COLLAID: enhanced tabletop-based system that captures student's interactions.* We built COLLAID (Martinez-Maldonado et al., 2011b), a system that extends an ordinary interactive tabletop to differentiate which learner is touching what, and which student is speaking, in a non-intrusive manner. It relies on an overhead depth sensor that associates each touch performed on the interactive surface with a specific student. It also includes a multi-directional microphone array that identifies the source of sound around the tabletop.

4. *Visualisations of tabletop collaborative interactions.* Another contribution is the design and validation of a set of visualisations of student's interaction data that can be shown to researchers, teachers or students themselves in order to foster awareness and reflection. In this thesis, the validation of these visual representations was mostly focused on offering teachers useful information about group work (Martinez-Maldonado et al., 2011d; Martinez-Maldonado et al., 2012f).

5. *MTClassroom: multi-tabletop classroom.* The MTClassroom (Martinez-Maldonado et al., 2013a; Martinez-Maldonado et al., 2012d) is a multi-tabletop classroom environment that consists of multiple interconnected instances of COLLAID that can capture live information of students while they work on a task. In this thesis, the MTClassroom was used to run authentic tutorials to investigate the different affordances of the data that can be automatically captured to help the teacher monitor the class in *real-time*, reflect on the tutorials after the class sessions and assess the enactment of the sessions based on their design.

6. *MTDashboard: teacher's dashboard.* MTDashboard (Martinez-Maldonado et al., 2013a) is a multi-platform controlling and awareness tool that allows a teacher to orchestrate key aspects of the MTClassroom. It offers a number of functionalities for the teacher to control the script of the classroom session and look at *real-time* visualisations of the on-task progress of each small group produced from the data captured by our enhanced tabletop environments.

7. *Analysis of collaborative interactions in a single-table learning setting.* From the data analysis aspect, this thesis contributes to the deep exploration of collaborative interactions by integrating data coming from multiple sources (touch interaction with the shared device, speech, characteristics of the artefacts and measures of learning). The studies in the single-table learning settings produced large amount of student's data that can be exploited by applying data mining and statistical techniques to discover meaningful patterns that can help differentiate high from low achieving groups.

8. *Analysis of collaborative interactions in the classroom.* Finally, the contribution of this thesis that is most strongly associated with real practice is the implementation of an authentic classroom and to perform analysis of student's interactions in parallel. This novel approach aims to present teachers with information in *real-time*, to help them decide which group to attend to next. The analysis also includes the discovery of trends in student's interaction data, making visible aspects of collaborative work of multiple small groups to teachers, where these aspects may not be easily seen without the use of technology.

A total of *eight datasets* were analysed for the studies that are described in this thesis. We analysed two external datasets collected from face-to-face settings with 57 and 18 students participating in small groups respectively (see details in Chapter 4). Then, three pilot studies served

to collect smaller datasets through our learning environment (CMATE). Between 15 and 20 students participated in each (details of these studies are presented in Chapter 5). Finally, we collected our larger datasets from our single-tabletop learning environment with 60 students (see Chapter 7) and multi-tabletop classroom tutorials conducted in two different courses, one with 236 and the other with 140 students in each (see Chapter 8).

## 1.5. Research Methodology and Validation Methods

In accordance with the multiplicity of research areas involved in each objective of the thesis, we started exploring available datasets to verify the feasibility of performing analysis of face-to-face collaborative interactions. Promising results and new areas for further development emerged after that exploration, thus motivating the conception of a novel conceptual and technological approach. This approach that was followed can be framed in terms of the *engineering method*. This consists of iteratively observing existing solutions, propose a *strategy for causing the best change in a poorly understood or uncertain situation within the available resources*, building the solution, measuring and analysing it, and repeating until no further improvement is required (Koen, 1985). We followed the next general phases proposed by Glass (1995), each associated with one or more thesis chapters (the order does not indicate strict time sequence, see Figure 1-2):

1. *The informational phase*. A literature survey of the current state of research was conducted on existing tabletop-based environments for learning and teacher support systems. In addition, we gathered information via reflection on the results of a deep analysis performed on student's data collected through existing learning systems of some partner research labs.
2. *The propositional phase*. The *conceptual framework* is formulated based on the literature review and exploratory research. The conceptual framework is further iteratively refined along with the analytical and evaluative phases that are described below. The design, implementation, and validation of the *technological* infrastructure prototypes was conducted and further refined in the following phases. In this phase the visualisations and teacher's dashboard were also designed and built.
3. *The analytical phase*. In this phase the developed solution (the conceptual framework and our tools) was operationalised, in order to conduct both controlled and classroom studies with real students and teachers. We collect substantial datasets that were further *analysed* mainly through statistical analysis, observations, data mining and process modelling techniques.
4. *The evaluative phase*. The testing and evaluation of the gathered datasets was conducted in this phase. The validation of our approach was mainly carried out by performing *quantitative evaluations* triangulated with qualitative assessments to aspect specific research questions.
5. *The technology transfer phase* (Kontio, 2001). This phase consists of taking an idea from laboratory to use of a mature product in the real world. This thesis conducted the initial steps towards the implementation of a multi-tabletop classroom using our data capture and analysis approach. We show the benefits of providing real teachers with key indicators of group work during and after the classroom sessions.

The multiple faces of the developed solution and the analyses of the tools, techniques and captured data are validated through different methods or the combination of them. Our main validation approach consisted of collecting, analysing, and interweaving data in a series of studies to provide a better understanding of the research problem (Creswell and Clark, 2006). In most of these studies we triangulated quantitative captured data and produced indicators, with qualitative information obtained from observations and human assessments, to confirm that the trends that might be automatically discovered are meaningful in collaborative learning contexts. This mixed method served to evaluate the different aspects of our approach, the developed tools and the implementation of the solution in the classroom.

The specific validation methods and their relationships with the contributions of the thesis are listed in Figure 1-1 (Validation), and can be described as follows:

- *Data mining and qualitative analysis of third-party datasets.* Three preliminary studies are conducted to explore the third-party datasets. Three different data mining were implemented to find patterns that may be indicative of group's level of collaboration. Then, qualitative measures of collaboration and group's performance are used to validate the meaningfulness of these patterns.
- *Iterative prototyping and observations.* The learning environment for concept mapping and the data capture system were iteratively built and validated in small pilot studies before being used in the larger scale studies in the single-tabletop setting and the classroom. Chapter 5 provides details of the final features of both systems.
- *Usability tests.* User studies were conducted to evaluate the usability of CMATE. Usability studies with a small number of users are effective to identify possible issues and allow for a dynamic iterative design process (Nielsen, 2000). However, these are not enough to evaluate a multi-user tool where the collaborative interactions are key conditions for effective computer support (Coppin et al., 2011). Therefore, we complement the usability tests with assessments of quality of the collaboration processes.
- *Accuracy evaluations.* The speech and touch unobtrusive capturing systems (COLLAID) were tested to assess how accurate they are to differentiate learner's input.
- *Evaluations with teachers (x3).* Teachers were involved both in the design and the evaluation of the tools presented in this thesis: the visualisation tools, teacher's dashboards and the multi-tabletop classroom.

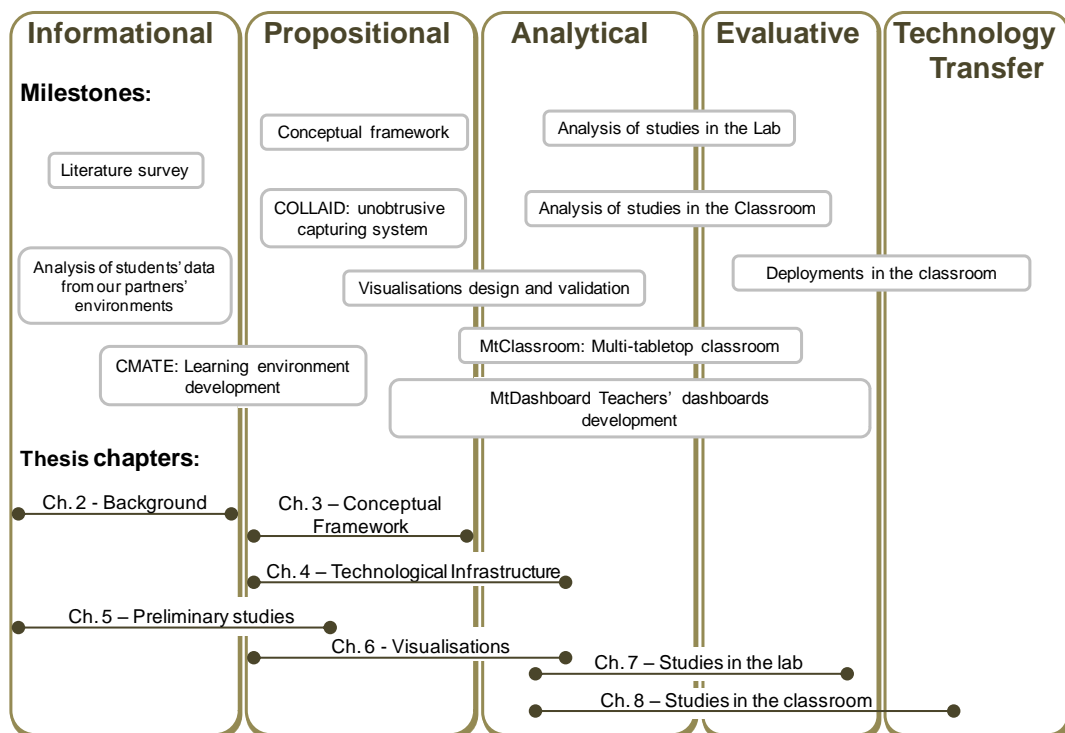


Figure 1-2 Research phases: associated milestones and thesis chapters.

- *Data mining, quantitative and qualitative triangulation.* A number of studies were conducted to analyse student's collaborative interactions in the lab and the classroom. In these studies there were multiple sources of data (application logs, speech detection, collaborative artefacts, individual artefacts, pre-post tests, teacher's observations and external observations)

that were triangulated in order to discover trends and patterns that can be associated with learner's strategies and collaborative processes.

- *Authentic tutorials (x2)*. Two university level tutorials linked with the regular curricula are conducted to demonstrate the feasibility of our approach in a real-world application with little intervention by the researcher.

## 1.6. Thesis Structure

This section describes the chapters of the thesis. Figure 1-3 illustrates the structure of the thesis and the publications associated to each chapter.

*Chapter 2* – Background - outlines relevant research on interactive tabletops in education, the growing usage of multiple tabletops in the classroom, the area of collaborative interaction analysis, and the exploration of previous work related to the learning environment mainly used in this thesis: tabletop concept mapping.

*Chapter 3* – Conceptual Framework – presents the approach proposed in this thesis. This consists of the foundations for designing a solution to exploit captured student's interactions at an interactive tabletop and analyse these through data analytics techniques to support teachers, researchers, designers or students.

*Chapter 4* – Exploring Other Datasets for Analysing Face-to-face Collaboration– describes three exploratory studies consisting in analysing pre-existing data sets of collocated collaboration using a multi-display and a shared-display environment. The outcome of the chapter is to create foundations for building an effective tabletop-based learning tool with unobtrusive data capture affordances. Two of the studies help determine whether it is possible to apply data mining and learner modelling techniques to produce group indicators. The third study investigates if the sequences of student's actions can provide insights into their higher level collaborative strategies.

*Chapter 5* – Tabletop Software and Infrastructure: CMATE and COLLAID – provides a detailed view of the reasoning behind the design of our collaborative learning environment and pervasive data capture system, building on the lessons learnt from the preliminary studies. From the technology perspective, these systems are the base of the main studies in this thesis. The chapter presents the design and evaluation of the collaborative learning tool CMATE; and describes the principles underpinning the design of the data capture system (COLLAID), the technology involved and the software infrastructure.

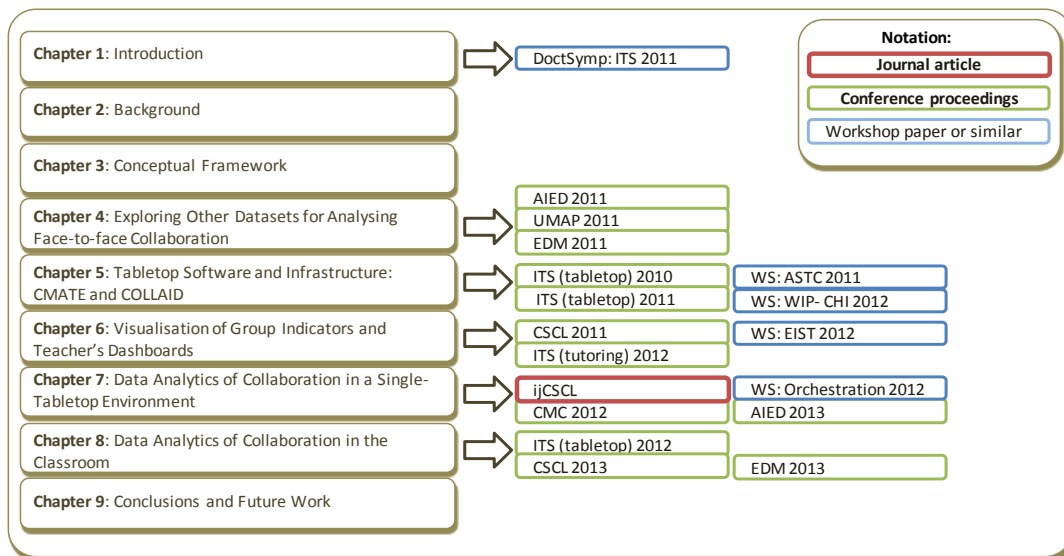


Figure 1-3 Structure of the research covered in this thesis and related published papers.

*Chapter 6 – Visualisations of Group Indicators and Teacher’s Dashboards* – explores key design requirements of the ways in which group’s interaction data can be shown to the teachers by visual means. This chapter presents the design of visual representations of symmetry of group activity, individual contributions, measures of collaboration, characteristics of the artefacts and the progress of the group task. It describes the evaluation of these visualisations and a number of teacher’s dashboards with real teachers; and provides insights into what type of information would be useful for the teacher to explore in the classroom and for after-class reflection.

*Chapter 7 – Data Analytics of Collaboration in a Single-Tabletop Environment*– describes the deep analysis of collaborative data of students working around a tabletop when the automatic data capture is performed under ideal conditions. The chapter presents the analysis of group’s interactions through artificial intelligence, data mining, user modelling and process mining techniques. This chapter contributes a novel experimental setting in which a series of learning activities are scripted in order to allow students to build artefacts both individually and in small groups. It also presents a detailed data analysis of student’s interactions captured from different sources, including application logs, identified speech, observations, learning tests and the learning products.

*Chapter 8 – Data Analytics of Collaboration in the Classroom* – presents the implementation of the thesis approach in an authentic classroom environment where a teacher can design and enact real university level tutorials that are part of the regular curricula, using multiple interactive tabletops. Our technological infrastructure automatically and unobtrusively captures rich contextual information that can help the teacher to assess their collaborative activities design, enhance their awareness of the group processes and obtain interesting patterns that distinguish high from low collaborative groups. This chapter: contributes the novel paradigm of allowing a teacher to both *control* and *monitor* multiple small groups performing collaborative work using interactive tabletops in the classroom by exploiting the data that can be captured through these; describes the design principles and the technological infrastructure that is used to build a multi-tabletop classroom; presents the data analysis performed through our enhanced classroom environment to reveal the benefits of exploiting student’s, teacher’s and classroom data; and presents the design and implementation of a teacher’s dashboard used in the classroom and the impact of delivering information of the group’s work on teacher’s attention and responses.

*Chapter 9 – Conclusions and Future Work* – revisits the contributions of the thesis in order to confirm each objective stated in section 1.6 is addressed. This chapter concludes the thesis with a discussion on the limitations of our approach, the current technological shortcomings that were considered and the promising research avenues for future research.

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## Chapter 2: Background

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*"If I have seen farther than others, it is because  
I was standing on the shoulders of giants."*

-Sir. Isaac Newtown

**Summary:** This chapter reviews the state of research at the intersection of the multiple disciplines that are the focus of this thesis. First, we present the principles of CSCL that this thesis builds upon, the concept of *classroom orchestration*, the current state of research of CSCL for face-to-face learning environments and indicators of collaborative learning. Then, the learning and technological contexts of tabletops in education are discussed. We review the current affordances of such technology to promote collaborative learning. We describe the previous research work on the use of tabletops under controlled conditions, the ways in which data from student's interactions can currently be captured, and the deployment of tabletops in the classroom. Next, we review work on the analysis of collaboration, mostly carried out on networked learning systems, through the production of indicators or visual representations of group interaction, and the application of data mining techniques on student's data. We finally highlight the open issues which this thesis aims to address through the provision of new ways to capture and analyse student's interaction data, and the deployment of supporting tools that can enhance teacher's awareness of the collaborative learning processes.

### 2.1. Introduction

There has been a steady growth of interest in the use of interactive tabletops in educational contexts. There has been significant research about several aspects of tabletop applications in learning contexts. This includes the exploration of novel ways to enhance learner's interaction, promote collaborative learning and support teaching activities. At the same time, there is a mature body of research on the automatic analysis of student's logs of activity, mostly recorded by networked learning systems that can help teachers enhance their awareness of learner's progress and collaboration levels. In spite of this, there has been little research exploring how student's data captured from face-to-face collaborative learning systems can help teachers and researchers understand the processes that distinguish high achieving from low achieving groups. As commercial tabletop hardware is becoming more readily available, tabletops may offer new opportunities to exploit these data by using data analytics to support the face-to-face collaborative learning activities designed and monitored by the teacher.

This thesis is interdisciplinary; therefore it requires a deep review of literature in different areas. Figure 2-1 shows some of the key elements that are relevant to this thesis and that are reviewed in this chapter. This background chapter provides a discussion of existing work that lies at the intersection of the study of CSCL in face-to-face settings, such as those supported by interactive tabletops (which are part of the focus of interest in the HCI research field), the use of technology to capture learners interaction data and also the application of data analysis techniques to discover trends in these captured data (EDM and data analytics). This thesis is also influenced by foundations of research on Group Cognition (Stahl, 2006), *classroom orchestration* (Dillenbourg et al., 2011) and the production of indicators of collaborative learning (Dimitracopoulou et al., 2004).

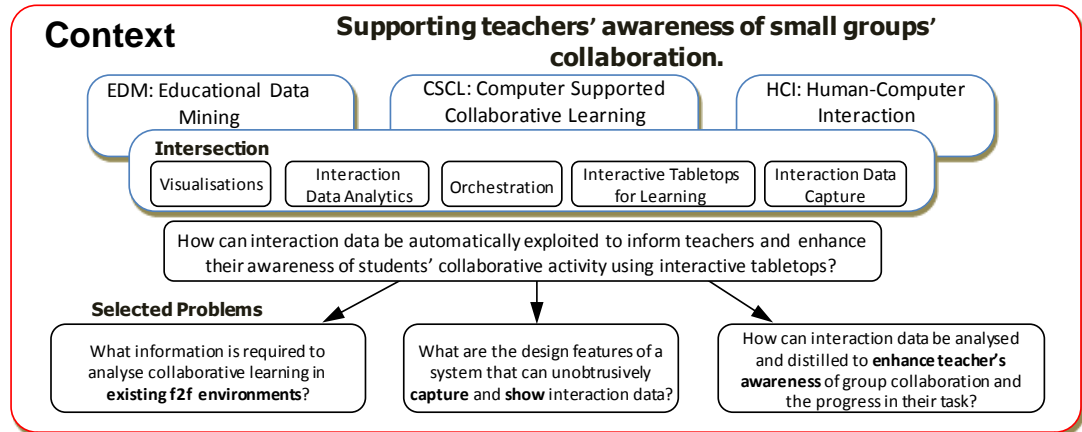


Figure 2-1 Partial diagram the represents the research context and the key problems this thesis addresses.

In accordance with the thesis statement presented in Section 1.2, this chapter reviews the current affordances of the interactive tabletops to both support face-to-face group activities and mechanisms to be aware of student's actions around the tabletop. This chapter also highlights the gap in research about the study of collaboration in collocated learning settings through the automatic analysis of student's interactions. Additionally, as stated in the thesis goals (Section 1.3), one of the main educational tools used in most of the studies presented in this thesis is the technique of concept mapping. By the end of this chapter we present a concise review of the application of concept mapping in collaborative environments and relevant concept mapping tabletop applications prototyped by other researchers.

This chapter is structured as follows. First, in Section 2.2 we discuss the relevant research in the field of collaborative learning and interaction analysis. Then, Section 2.3 reviews the research on the use of interactive tabletops for learning, focusing on three aspects: their relation to CSCL theories and practices; collaboration data analysis; and their use in the classroom. Third, Section 2.4 describes previous work that has addressed the analysis of collaboration using learning analytics and data mining techniques. Fourth, Section 2.5 presents a review of the knowledge representation technique of concept mapping and the use of interactive tabletops to build concept maps. Finally, we list the open issues that are addressed in this thesis and also those that are beyond the scope of our approach in Section 2.6.

It is important to highlight that parts of this literature survey have already been presented by the author in different publications (see Publications during candidature). We also note that some original work presented in this thesis explored new ground especially at the intersection between the research fields involved. Some similar work by others reported in this chapter was presented after, or built on, our research work. We specify, accordingly, when this is the case.

## 2.2. Collaborative Learning and Interaction Analysis

This thesis draws on considerable work in three aspects of CSCL. First, we build on a scaffolding theory for the design of an approach that takes account of the benefits of collaboration for both externalisation of student's perspectives and internalisation of new knowledge. We chose the constructivist theory of Group Cognition (Stahl, 2006) as we consider the tabletop hardware as just a partial mediator of knowledge, and the artefacts that are build through this medium as true containers of student's shared understanding. Second, we draw upon significant previous work on the automated analysis of student's collaborative interactions to generate indicators of collaborative learning. That has mostly been done through networked systems. Third, part of our approach consists in supporting teachers in fostering student's collaborative learning, and integrating our tabletop systems into the classroom. This is grounded on principles of *classroom orchestration* (Dillenbourg et al., 2011), specifically on regulation, awareness, planning, design and the role of teachers in and out the classroom.



### 2.2.1. Group Cognition: Model of Collaborative Knowledge Building

The theory of Group Cognition (Stahl, 2006) considers small group activity as a process that can be focused on constructing new understanding where the learning and teaching contexts are very important. For Group Cognition, meaning is created across the utterances by different learners working in a group and it is also contained in the abstract and physical artefacts created by learners. Group Cognition takes account of other theories that have gone beyond the classic paradigm of considering cognitive models that represent individual learning processes in isolation. These include the theories of Mediated Cognition (Vygotsky, 1978), Distributed Cognition (Suchman, 1987; Winograd and Flores, 1985) and Knowledge Building (Scardamalia and Bereiter, 2006). This subsection is mostly based on Stahl's theory of Group Cognition (Stahl, 2006).

Group Cognition can be defined as the result of effective *collaborative knowledge building*. Collaborative knowledge building (Scardamalia and Bereiter, 2006) stresses supporting interactions among students themselves rather than human-machine interaction, with the teacher working more in a facilitating than an instructing role. It entails more than simple socialisation. Knowledge building implies that learners develop some kind of knowledge in the form of theories, models, conceptual maps or other physical artefacts. While individual cognition is hidden, private and based on mental processes; Group Cognition has to be publicly available, generating more evidence of understanding-making.

The definition of the dimension of collaboration can be very broad. When talking about collaboration it is important to differentiate between the context of the group, such as dyads working together, small groups of 4 or 5 persons working on a semester project, or communities of knowledge that communicate and build new knowledge over very long periods of time (Dillenbourg, 1998). Size and timing are key aspects that define the kind of collaborative situation to be considered. Group Cognition theory focuses on small group knowledge building processes that are not visible in the same ways as monologues, dyads or big communities. For this reason, in this thesis we focus on small groups with more than 2 learners in each as the main unit of analysis.

Following these theories, a group of people working collaboratively can externalise and negotiate their different viewpoints. Sometimes the flux of interactions results in external artefacts such as texts, conceptual maps, diagrams, sculptures and other objects. These social artefacts embody the group's understanding. Figure 2-2 illustrates the basic model of Group Cognition building on Stahl's model. This model has two main "cycles": the personal understanding (1) that occurs inside individual's mind and the social knowledge building cycle (2) which includes all the sub-processes that may be present when building social understanding. In face-to-face interactions, this process can generate a huge quantity of cognitive artefacts in short periods of time. Group members have to articulate their thoughts to convince others or to explain their point of view. Learners, by externalising their personal understandings, integrate their knowledge with the group understanding as a whole to then appropriate some of it into their own personal understanding (see blue lines in Figure 2-2). By externalising their thoughts, potentially, they leave digital traces of the collaborative knowledge building process. When a person negotiates, shares or revises their standpoint, they may appropriate artefacts to support this, leaving more evidence of the collaboration process. It is these digital traces of the collaborative process that we aim to make use of.

One of the main elements of group knowledge building that influences the work presented in this thesis is the notion of *perspectival computer support*. Learners interpret problems in their environments using conceptual frameworks that they developed in the past (Roschelle, 1996). In challenging cases, problems can require changes in these frameworks. Such conceptual change is essential for learning and can be facilitated while learning by collaborating. Different students construct different views, compilations of facts and arguments that differ depending on the social situation. Even a single person can have multiple perspectives or have perspectives derived from others. So when students aim to collaborate to build a joint solution, they should negotiate the intertwining of these perspectives. The exploration of different levels of perspectives can lead to richer models of the group, including: the group as a whole, personal perspectives and comparisons between perspectives.

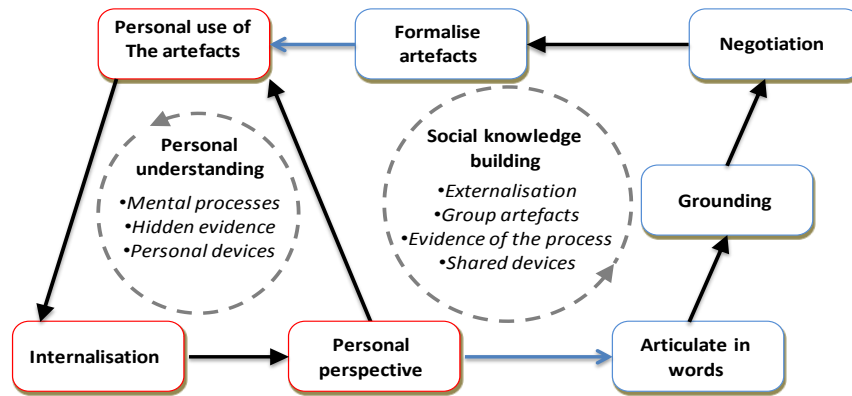


Figure 2-2 Diagram of the collaborative knowledge building process. Adapted from (Stahl, 2006).

For the theory of Group Cognition, collaboration technology provides enormous potential to identify many-to-many interactions by helping mediate student's communication and keeping logs of the activity. The technology should allow the articulation of student's ideas and, at the same time, provide the means to preserve them in *tangible* forms. As the CSCL medium becomes more sophisticated, it is more important for the system and teachers to know who is doing what, what has been done and how to find existing information. Group Cognition defines a set of aspects that effective collaborative learning system (groupware) should aim to support:

- allowing students to express believe and clarify disagreements,
- providing the opportunity for creating artefacts that contain the shared knowledge,
- allowing the discussion of desired modifications to the task or the collaborative process, and smooth transition to perform such modifications,
- integrating with other educational software,
- delivering information automatically when it may be useful,
- providing the opportunity of signalling readiness (to accept or publish the final artefact), and
- allowing the formulation of knowledge by the end of the activity.

### 2.2.2. Indicators of Collaborative Learning

Following from the theory of Group Cognition, Stahl (2006) stated that clues about the learning that took place while the group of students collaborated can generally be found by analysing the externalised verbal dialogue and the student's products (artefacts). The technological infrastructure may be able to capture key information about this student's collaboration. However, face-to-face interaction is a rich type of group work in which it may be possible to observe different kind of gestures, intonation, hesitation, turn-taking, overlapping, facial expressions, bodily stance, textual context and any produced artefact. From a research or teaching perspectives, it is important to define the key interactions that might be useful to focus among all this gathered student's data.

*Computer Based Interaction Analysis* is the emerging discipline that has been targeting this issue (Dimitracopoulou et al., 2006; Soller and Lesgold, 2007; Soller et al., 2005). This has focused on producing indicators of collaborative learning to analyse and provide support, or enhance awareness of the group processes. A number of network-based technologies have emerged over the last decades to enable learners to interact and learn collaboratively. One method adopted by systems that support collaboration involves the provision of coaching or self regulation tools. For this, the state of interaction is evaluated with respect to a desired state, and then remedial actions may be

proposed in order to reduce discrepancies between these states (Soller et al., 2005). The remedial actions can be directly targeted to the students, notified to the teachers or to certain technologies that can perform actions to foster self-assessment, regulation or support (Dimitracopoulou et al., 2004). The process primarily starts with the generation of indicators of group activity that can be derived from the very complex interactions that occur through the collaborative systems. The results of the interaction analysis can be shown to the participants in the learning activities in a graphical, numerical or text formats (mirroring); or interpretable by artificial intelligence tools that can perform corrective actions automatically (guiding) (Soller et al., 2005).

The main phases involved in the computer-based interaction analysis process are illustrated in Figure 2-3 and described as follows. First, students interact with the learning environment. At different moments of the activity, they can interact with the environment individually, as a group or between themselves outside the technology-based learning tool. Additionally, a teacher may intervene or just supervise the collaborative activity. In order to analyse student's interactions, the target data to be analysed are *selected and filtered*. Most of the time the raw data needs to be *pre-processed* to obtain meaningful information of learners actions. Then, the proper data *processing mechanisms* analyse and aggregate the data to produce a set of *indicators of group collaboration*. These indicators are the key product that can be used to generate visualisations, recommendations or models that can be used by additional tools to provide enhanced guiding. With these indicators, designers can build systems that reflect student's information, that monitor the state of interaction or that offer advice (Soller et al., 2005).

An *indicator* is a variable or variables that describe a specific aspect the learning activity, the interactions, the learning product or the collaboration process. Each indicator is defined by a main concept (Dimitracopoulou et al., 2004), for example division of labour, intensity of the collaboration, participation rate, equality of the interactions or individual performance. These indicators can be used to promote awareness, assessment or evaluation. And can be used either *in real-time* or for *post-hoc* analysis. Their usage in *real-time* generally is needed for situations where participants in the learning activity (teachers and students) can observe the information provided by the indicator, then make an immediate change in the learning or collaborative processes. This mostly includes mirroring systems or tools that enhance teacher's awareness. The *post-hoc* usage implies that the final user will have the time and interest to inspect the output of the analysis after the learning activity is finished. In this case the observers of the learning process are quite often teachers, designers or researchers.

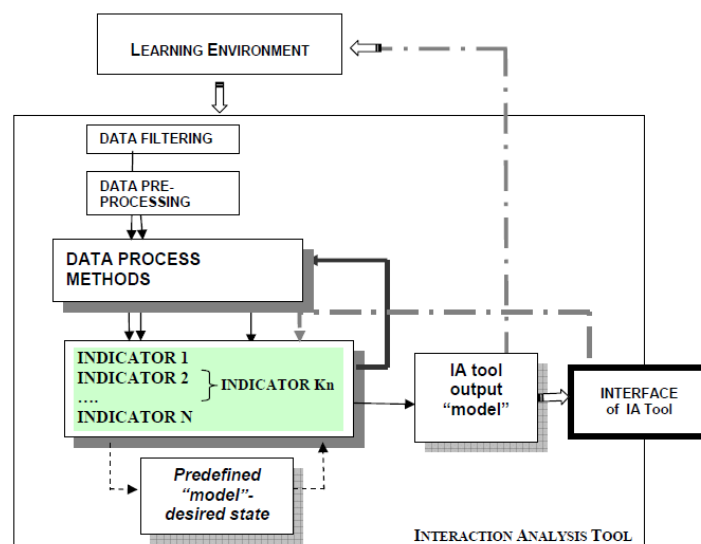


Figure 2-3 Generic Interaction Analysis processes (Dimitracopoulou et al., 2006).

In this thesis we investigate and generate a number of these indicators of interaction. However, we drive most of the design of these based on the emerging concept of *orchestration*. We review the state of this work and discuss the implications for our research in the next section.

### 2.2.3. Classroom Orchestration

The third principle presented in this section is *orchestration*. It is defined in terms of the design of learning activities and the *real-time* management of the classroom resources, learning processes and teaching actions (Dillenbourg and Jermann, 2010). Orchestration in the context of CSCL can be described as a loop of awareness and regulation: the teacher monitors the state of the classroom, compares its state to some desirable scenario, and performs actions to reach such a desired state accordingly (Dillenbourg et al., 2011). This loop is very similar to the one stated by Soller et al. (2005) that was described in the previous section, but applied to networked collaborative systems and the analysis of student's data.

The orchestration approach defines two key required processes: *state awareness* and *workflow manipulation*. According to this, the technology itself does not need to perform complex analysis or automated actions, but instead it should just provide *filtered* key information about the classroom state leaving the diagnosis of such data to the teacher (Dillenbourg et al., 2011). Dillenbourg & Jermann (2010) defined a number of factors that provide a teacher-centred and integrated view of technologies for *classroom orchestration*. Next, we describe 10 out of 15 of these key factors that directly apply to the learning context targeted in this thesis:

1. *Teacher-centred*. Teachers should design the learning scenario, the activities and lead the collective management of resources in the classroom.
2. *Flexibility*. Teachers also should be able to change the learning scenario or the script if needed, and the technology should provide the flexibility to allow this.
3. *Control*. The technology should provide teachers with the means to keep control over the class resources and students.
4. *Integration*. The technological resources should be accessible and consistent in all individual, small group or class level activities. The products of student's activity should also be accessible after class.
5. *Linearity*. The method is a simple sequence of activities that almost all students will perform at almost the same time. In this way it is easy to be explained to the students.
6. *Relevance*. The activities should be designed according to their impact as specified in the regular curriculum.
7. *Physicality*. In contrast with other models that mostly address networked learning spaces, *classroom orchestration* refers to the concrete physical space in the classroom.
8. *Awareness*. The technology should help teachers to be aware of the state of student's activities and any trend or pattern of behaviour that may be relevant.
9. *Minimalism*. The functions offered by the technology should be simple but effective, providing services that are not already provided by other tools in the classroom or that do not empower classroom activities compared with not having such technology.
10. *Sustainability*. The approach can be easily repeated and adopted by the teacher and be implemented in the classroom.

Prieto et al. (2011) performed a comprehensive analysis of literature on orchestration, even beyond the classroom setting. Figure 2-4 shows the aspects of orchestration that are considered as *relevant*. However, in this thesis we are limited to those aspects that are associated with the theories of Group Cognition and Computer-supported collaboration analysis described in Sections 2.2.1 and 2.2.2 respectively. These aspects are marked in Figure 2-4 with yellow borders and defined as follows:

1. *Design/planning*: A key component of orchestration is planning the learning activities that will be monitored and coordinated in the classroom. Our approach takes into account the information that can be captured by the tabletops to inform teachers with key indicators that they can use to re-configure the class script or to re-design the activity for future sessions.
2. *Regulation/management*: This aspect includes the management and control of the resources available in the classroom (technological, physical and human) to achieve the objectives of the learning activity. In this thesis we address this by providing the means for the teacher to have the control of the tabletops and the whiteboard in the classroom.
3. *Adaptation/flexibility/intervention*: Another aspect of the definition of orchestration is that both the learning scenario and the technology have to allow changing and adapting the script or the plan of both the current instantiation of the classroom and the unplanned events during the enactment of the learning activities. This can be done by teaching mechanisms or through the technology itself.
4. *Awareness/assessment*: Possibly one of the main aspects of orchestration that our approach contributes to is to provide teachers with the possibility to perform more effective interventions in response to the classroom context and emergent changes by supporting their awareness. Assessment is an aspect that falls beyond the objectives of this thesis but the same group indicators that can be generated by our tabletop approach may be used for evaluation.

The most significant work on orchestration at a multi-tabletop classroom has been previously reported by AlAgha et al. (2010). The authors presented an interactive tabletop that can help a teacher monitor multiple groups working on a task performed at up to four tabletops. Dillenbourg et al. (2011) presented tools to enhance teacher's awareness of the progress of small group activity, with coloured lamps and the use of paper cards to control interactions with tangible interactive tabletops. Another example is given by Twiner et al. (2010), who presented work on *classroom orchestration* by providing tools for the teacher to control the class using an interactive whiteboard. A more detailed description of the deployment of multiple orchestrated tabletops in the classroom is provided in Section 2.3.5. The link between our approach and *classroom orchestration* is mainly addressed in Chapter 8, where we introduce the implementation of data analytics in the multi tabletop classroom.

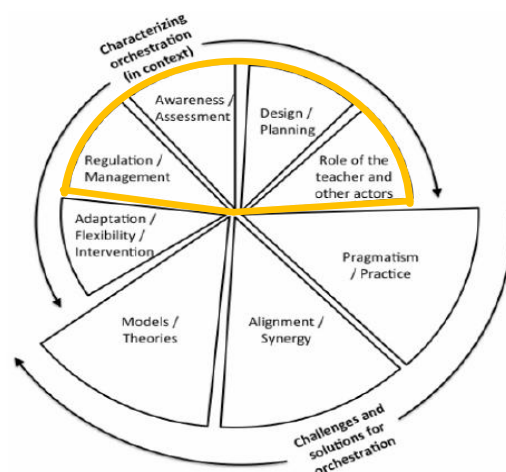


Figure 2-4 The multiple faces of orchestration (Prieto et al., 2011).

## 2.2.4. Section Summary

This section provided a review of three key referent theories or paradigms that provide scaffolding for the framework and the learning environments to be presented in thesis. The most general approach our work builds upon is the theory of Group Cognition that was introduced in Section 2.2.1. We reviewed Stahl's work (2006) to define the type of collaborative scenario our approach

aims to support and to drive the design of the technological tools and the learning activities. Through this theory, we know that an effective and unobtrusive data capture systems needs to be operated automatically to produce indicators of collaboration. We also defined the context of the study with tabletops, the learning tool (concept mapping) and the collaboration dynamics we can expect. In Section 2.2.2 we reviewed the support for collaborative interactions from a different but overlapping perspective that we called *computer-supported collaboration analysis*. This paradigm highlights the automation of the analysis of student's data. Even though this approach mostly derives from non-face-to-face research, the usage of data to mirror, guide or enhance reflection through the generation of indicators of interaction is a valuable resource for our approach. Finally, Section 2.2.3 provided a brief description of orchestration and the aspects that are relevant for our aim.

## 2.3. Tabletops for Learning

Our work involves the use of emerging pervasive shared devices in the form of multi-touch interactive tabletops like the one shown in Figure 2-5. We argue that these devices can offer new possibilities to both support collocated collaboration and capture the digital footprints of student's interactions. If this can be achieved, these student's data can be exploited to analyse the collaborative process in radically new ways. Conventional tabletops are natural working spaces around which people discuss and work together on activities that may require the expertise or consensus of all group members. Interactive tabletops offer an augmented shared space in which all students have equal opportunities of interaction with digital tools, content and artefacts, in addition to a natural space for face-to-face discussion, rich group awareness and instant communication (Dillenbourg and Evans, 2011). The first two parts of this section focus on two main features of interactive tabletops: (i) their affordances to support collaboration and collaborative learning, and (ii) the current state of the tabletop technology that can enable the learning systems to be aware of student's activity. Then, we present a number of tabletop-based learning applications focused on promoting collaborative learning. Thereafter, we describe the initial research work that has explored ways to exploit some data that is currently captured, mostly manually, from tabletop environments. Finally, we conclude the section with a review of deployments of tabletops in the classroom.



Figure 2-5 A multi-touch interactive tabletop

### 2.3.1. Tabletops Affordances to Support Collaboration and Collaborative Learning

Interactive tabletops can enrich a typical face-to-face setting by offering a horizontal, and relatively large, display interface suitable for group work. It enables users to directly interact with digital information, or even tangible objects, while maintaining mutual awareness and direct communication (Müller-Tomfelde and Fjeld, 2012). Interactive tabletops are good examples of disappearing computers (Streitz and Nixon, 2005), because they convey the impression that the computer has been taken out of their usual container and their components are embedded in the environment (Müller-Tomfelde and Fjeld, 2012). From the user's point of view, tabletops allow

learners to interact directly with objects instead of using the keyboard or mouse, and each can be aware of other's actions. Users can combine the advantages of the physical setting provided by traditional around-the-table meetings with the possibilities that a digital environment can offer.

Having stated the positive features of tabletops, there has also been an over-expectation of tabletop affordances (Müller-Tomfelde and Fjeld, 2012). Similarly to other learning technologies, tabletops themselves do not provide a direct improvement in learning or collaboration. But they do provide novel ways to design activities that teachers and researchers can take advantage of, to enhance instruction (Dillenbourg and Jermann, 2010). Figure 2-6 shows a curve in the evolution of tabletop technology over recent decades and the expected slope of gradual adoption of interactive tabletops especially for collaborative activities (Müller-Tomfelde and Fjeld, 2010).

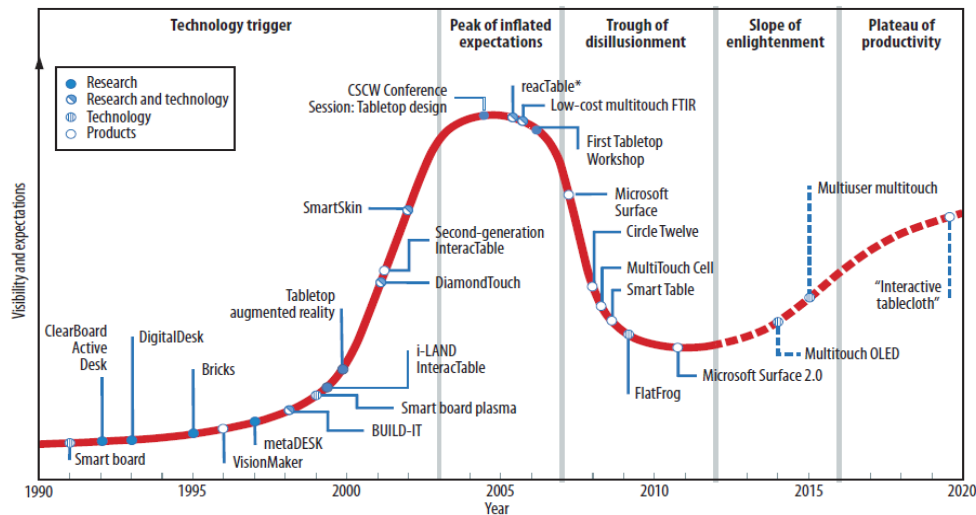


Figure 2-6 Evolution of tabletop research according to Müller-Tomfelde & Fjeld (2012).

Regarding the educational settings, an obstacle for effective use of *personal* computers in the classroom is that these tend to make it more difficult to promote face-to-face collaboration due to their small display and single input (Morgan and Butler, 2009). By contrast, tabletops have significant potential to support a number of different aspects of education, spanning from providing a shared and enriched interactive space through which students can have access to digital content with equal opportunities of participation while they build a joint solution (Kharrufa, 2010; Morris et al., 2005; Schneider et al., 2012; Stock et al., 2008), to supporting teachers by improving their awareness or their control over a class (AlAgha et al., 2010; Hatch et al., 2011; Mercier et al., 2012). Nonetheless, a number of researchers (Dillenbourg and Evans, 2011; Higgins et al., 2011; Müller-Tomfelde and Fjeld, 2012) have warned about the initial overstated enthusiasm triggered by the novelty of interactive surface technologies that has not been followed by broad adoption of such devices for real-world applications. Therefore, there are still unanswered questions about the ways teachers can best take advantage of their affordances (Dillenbourg and Evans, 2011). Research still needs to be done to help teachers shape these technologies to match learning objectives.

However, as stated above, the technology itself does not provide a direct enhancement for ways to collaborate in learning contexts, because their use mostly depends on the instructor's teaching and learning goals (Cuban et al., 2001; Dillenbourg and Evans, 2011). Interactive tabletops are actually not very ergonomic for certain activities reducing their applicability for long term activities in which learners should mainly focus on the interactive device (Benko et al., 2009), for example, in activities that involve reading large amounts of text (Morris et al., 2007) or day to day desktop tasks (Wigdor et al., 2007). Even though interactive tabletops have received considerable attention from researchers they still have unsolved problems to present large amounts of text (Benko et al., 2009; Hinrichs et al., 2007). They also have unsolved challenges when there is a need to show digital elements where orientation is very important. Other more technical aspects, such as the limited screen resolution of today's hardware and the physical limitation of precise input (for finger touch), can make the use of tabletops challenging for certain types of tasks with some



interfaces. However, tabletops can be effective in other activities where the face-to-face interaction between users is as important (or even more relevant) as the interaction with the digital medium.

Benko et. al. (2009), in a survey of design researchers and developers, highlighted the main limitations of tabletops, in order of importance: the provision of a keyboard for text entry (both physical and digital keyboards presented problems when shown on the display or attached to the tabletop environment), the availability of standard applications (desktop standard applications are very often not suitable for horizontal devices and the market of tabletop users is not yet large enough for sustainable development of commercial tabletop applications), precise pointing (which can be improved with the use of stylus with the detriment of the advantage of using fingers only), and the above-mentioned issues with ergonomics (with users complaining of neck strain) and orientation (especially for reading text). By contrast, the same survey indicated that tabletops offer advantages over traditional personal computers, including direct touch input (for long-term personal use and foster collaboration awareness), large display and interactive areas (especially for collaborative scenarios), and their horizontal orientation (to provide space for users to collaborate in different tasks).

The rest of this sub-section presents a short review of research work that has explored the advantages of tabletops orientation, input styles and opportunities for user's participation, in the context of collaboration. One of the initial explorations of the affordances of tabletops for collaborative creation was conducted by Rogers et al. (2004) by comparing them with vertical interactive displays that are more commonly available in current classrooms. Even though the technology used at that time did not strictly allowed natural interaction with the interfaces (users had to share an electronic pen to interact with the surface device as shown in Figure 2-7), the study helped to shed some light on the advantages and limitations of interactive tabletops for egalitarian group work. The authors found that the tabletop display allowed users to be more aware of other user's actions which resulted in improved idea generation. By contrast, the vertical interface offered less space for collaboration, with users following a specific user leading the interaction at a time. A follow up study by the same authors (Rogers and Lindley, 2004), and a more recent study on collaborative brainstorming (Clayphan et al., 2011), confirmed these findings by demonstrating that using interactive tabletops, in isolation or combined with other devices, such as vertical displays (Figure 2-7, right), provide the opportunity for users or learners to interact more equally as required. They also found that using tabletops may trigger mutual interactions that can lead to improved generation of ideas and awareness of other's actions, which cannot be achieved in the same degree if vertical displays are used in isolation.

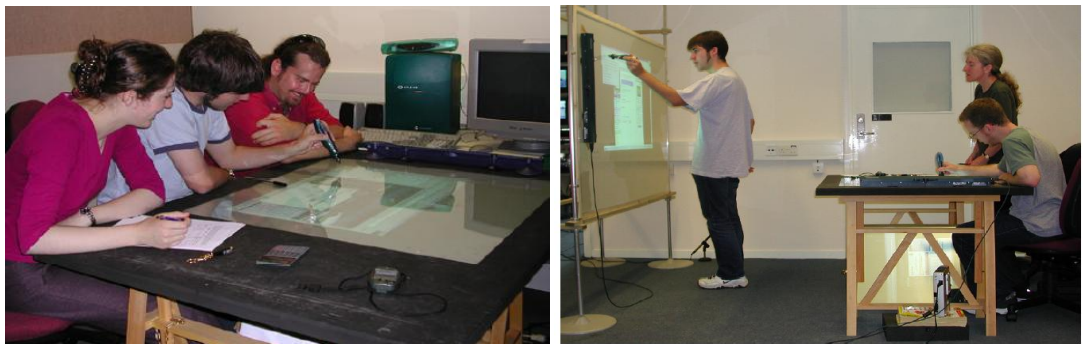


Figure 2-7 Comparing vertical and horizontal interactive displays. Left: tabletop condition. Right: using both displays at the same time (Rogers and Lindley, 2004).

A subsequent study explored the benefits of using tabletops for group work compared with a common scenario where a shared laptop is an aid to collaboration and conversation (Rogers et al., 2009). This research reported that tabletops provide users with more equal opportunities of participation, not only in physical input but also in the distribution of the produced verbal utterances. By contrast, sharing a single input device (mouse and/or keyboard) forces groups to choose roles and verbally negotiate the actions that need to be performed to complete the task. However, this hinders the possibilities of contribution for users who do not have control of the input devices. Indeed, there is not total agreement on which way it is better to collaborate. A similar study



comparing similar settings found that the tabletops may allow students to work separately (given that all students can work in the area near to them), without maintaining mutual awareness, while with sharing a laptop at least users are forced to pay attention and discuss how to use the mouse and keyboard (Do-Lenh et al., 2009).

We now list research explorations that have highlighted the tabletops affordances for multi-touch input compared with other interaction techniques for horizontal devices. First, Hornecker et al., (2008) demonstrated that there are significant differences between multi-touch and multi-mice input in the tabletop. These two settings are shown in Figure 2-8. Mouse input tends to favour a higher degree of division of work and a less dynamic way to negotiate and deal with interference (simultaneous interaction of 2 users with the same resource). By contrast, multi-touch input resulted in more positive workspace awareness and an improved coordinated interaction within groups in terms of more frequent shifts of control. Multi-touch input favours simultaneous work or work in parallel. Another interesting finding is that in multi-touch tabletops users experienced more interference when they tried to touch objects that were very close to each other since there is not enough space for multiple hands to work in the same region. However, most interference can be resolved smoothly and even with non-verbal communication. This study suggested that the horizontal disposition of the interactive tabletop is not the only factor that affects group's collaborative behaviours but also the multi-touch input.



Figure 2-8 Comparing input style. Left: Direct touch. Right: mouse clicks (Hornecker et al., 2008).

Harris et al. (2009) further investigated the input of single and multi-touch affordances of tabletops on collaboration in a learning scenario. Results showed that there is not much difference between the two conditions in the frequency and equity of interactions, but the input influences the nature of student's discussion. With the multiple-touch tabletop, students tend to talk more about the task; while with the single-touch tabletop, the main topic of discussion is about turn taking.

Schneider et al. (2011) compared the impact of the way in which information is presented at an interactive tabletop (as digital content or with physical tangible tokens) on the degree of collaborative learning (Figure 2-9). The authors indeed found no difference in the ways students collaborate. However, the use of tangible objects at the tabletop promoted exploration and playfulness by students in building a solution collaboratively. Therefore, the authors argue that for some specific tasks it might be convenient to enhance the collaborative experience using physical tokens rather than digital virtual objects.

Most of the projects presented in this section studied the ways users collaborate when using tabletops compared with other shared devices. They mostly had a pure user interaction focus. Moreover, their qualitative analyses modestly grounded on theories of learning or collaboration. Their findings are hard to generalise given the restricted and controlled conditions they imposed. However, they provide a good indication that the tabletops themselves do not provide a direct benefit for collaboration. Rather they may enable users to define their strategies in case they decide to collaborate, and a new space for designing collaborative activities and interactions.

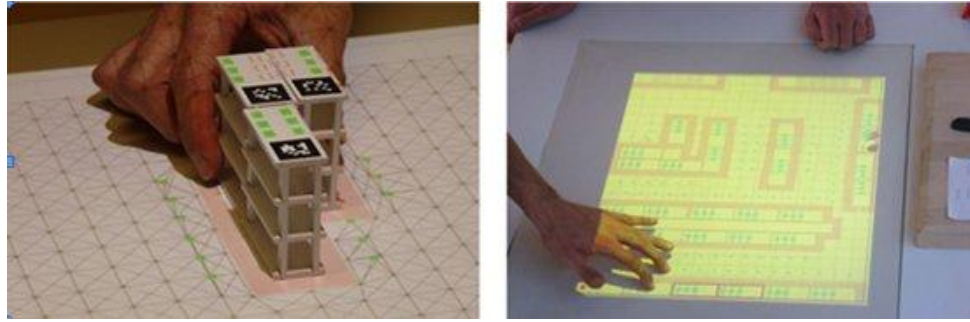


Figure 2-9 Comparing tangible and virtual objects (Schneider et al., 2011).

### 2.3.2. Tabletops Affordances for Data Capture or Context-awareness

Another category of affordances of tabletop environments, that has received, is the possibility of using them, along with other technologies, to build context aware table systems, which can be used in learning environments like those in this thesis. Streitz et al. (2005) envisioned that an intelligent ubiquitous environment should collect contextual data and aggregate these data to provide and communicate the resulting information, in an intuitive way, so that users can comprehend it easily, for guidance and subsequent actions determined by the users themselves, so they can maintain the control of what to do next.

This section provides an overview of the increasingly diverse mechanisms for touch identification, user identification and some systems that enhance a tabletop's awareness of user proximity. For each, we show the implications of applying them in authentic environments following the principle of *unobtrusiveness*. First, we define the key affordances of this kind of systems:

1. *User differentiation (touch identification)*. This refers to the capability of the tabletop system to associate each touch on the interactive surface with the user who performed that touch. For this, users are at least differentiated, even when the system does not know the identity (name or user model) associated with each. The identification is determined by an external system or by human judgement. Most of current tabletop solutions in this review fall into this category.
2. *User identification*. It refers to the ability of the system to associate each touch with the user who performed it, and the user is somehow recognised or authenticated by the system.
3. *User localisation (proximity, location and speech awareness)*. The system, in order to offer full user identification and activity tracking, should maintain awareness of user's proximity and location around the tabletop to associate their touches and higher level actions with them. If possible, the system should be aware of other user's actions, such as when they speak.

Next, we review key solutions for each of the three categories.

#### *User differentiation*

In collaborative situations it is very important that students have some indication of their individual contribution to the group task if the teacher or facilitator aims to be able to monitor their progress (Morgan and Butler, 2009). Mirroring the unobtrusively captured differentiated contributions of group members is also an important element of collaborative learning to foster equality or assessment of the group outcomes (Bachour et al., 2010; Kay et al., 2006; Upton and Kay, 2009).

The most widely used system for user differentiation in the community of tabletop research is the DiamondTouch<sup>1</sup> (Dietz and Leigh, 2001). DiamondTouch can distinguish users even when several of them touch the tabletop surface simultaneously. It does this by transmitting signals through the table itself. These signals are coupled through the user's bodies by creating a loop with sensors placed on their chairs. When a user touches the table, the circuit gets closed, identifying the parts of the table each user is touching. Figure 2-10 shows a representation of the arrangement of the hardware. The system provides very accurate user differentiation since, ideally, there is little chance of a mistaken touch given that user's bodies are used to establish an electrical circuit. However, in order to get user identification the natural movement of people around the tabletop is restricted, by forcing them to remain seated. This approach has worked well under controlled conditions.

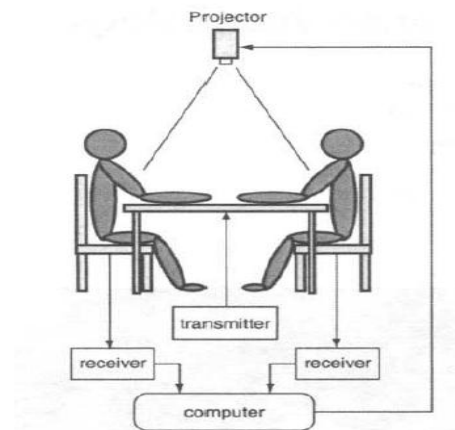


Figure 2-10 Diagram that portrays the main components of the hardware of the DiamondTouch that provides touch sensing and differentiation (Dietz and Leigh, 2001)

A second effective way for an interactive tabletop hardware to differentiate users is by using small pieces of hardware that people can grab or wear on their hands or arms. An approach that has proved successful in providing this affordance is the use of pen pointers through which users interact with the surface. Some examples include the work done by Collins (2008) and Kharrufa (2010). The first approach adapted Mimio pens<sup>2</sup>, which are commonly used on vertical devices, to build a non-multi-input pen-based tabletop using overhead projection. The second example approach adopted a similar vertical system, called Promethean Activboard<sup>4</sup>, which is a pen-based device that allows for multiple and differentiated input.



Figure 2-11 Hardware attached to user arms that afford user differentiation. Left: IdWristbands (Meyer and Schmidt, 2010). Right: fiducially tagged gloves (Marquardt et al., 2010)

IdWristbands (Meyer and Schmidt, 2010) consist of a series of infrared LED's, placed on a wristband worn by the user. These transmit a specific blinking pattern in order to associate touches with the corresponding user's arm (see Figure 2-11, left). Marquardt et al. (2010) developed fiducially

<sup>1</sup> <http://www.merl.com/areas/DiamondTouch/>

<sup>2</sup> <http://www.mimio.com/>

<sup>4</sup> <http://www.prometheanworld.com>

tagged gloves that enable the tabletop to both distinguish between one person's or multiple people's hands, and more specifically, to identify the parts of a hand touching the surface, including user's fingertips, knuckles, palms, sides or backs of the hand (see Figure 2-11, right).

Even though pens, gloves, and wristbands can offer effective affordances for user differentiation in tabletop systems, they impose limitations in the interaction space and critical restrictions that make these solutions hard to implement in authentic environments. In the case of pens, these have proved to be effective when the activity performed on the tabletop requires higher level of input precision. But the naturalness of direct-touch interaction is better in terms of efficiency and user preference (Brandl et al., 2008; Frisch et al., 2009). In the case of wearable gadgets, these are not practical in real learning scenarios such a classroom (Morgan and Butler, 2009).

A third approach to provide touch differentiation has been explored after we developed our mechanisms for user differentiation presented in this thesis and in previous publications (Ackad et al., 2012; Martinez-Maldonado et al., 2012b; Martinez-Maldonado et al., 2011b). This recent trend, pioneered in our approach, mostly consists of using vision systems below or above the interactive surface. Zhang et al. (2012) developed an approach for discriminating touches on a vision-based tabletop by guessing the finger orientation according to the features of the shape of the touch analysed with a machine learning model from images taken by the tabletop itself.

Similar approaches to ours were presented a year after our first publication. These basically consist of using an overhead Kinect Camera<sup>1</sup> to detect touch interaction and objects over the interactive tabletop. The dSensingNI (Klompmaaker et al., 2012) framework is capable of tracking user's fingers and hands to provide advanced multi-touch interactions on the horizontal surface or tangible objects. Therefore, the focus of this approach is not the user differentiation. A similar approach is Extended Multi-touch (Murugappan et al., 2012). This system enables touch, finger and hand posture detection; and also to distinguish between different users and the hand they use. The validation of this approach was conducted on a scratchpad and pen-touch sketch applications. However, none of these three examples have yet to be used in real settings, beyond the laboratory.

Lastly, a promising approach is starting to be explored using capacitive sensing to differentiate users in small handheld devices (Harrison et al., 2012). This exploits the biometric electrical properties of individuals to differentiate them. This approach still needs further evaluations and to be adapted to larger size touch displays to overcome the limitations of the systems described above.

#### *User identification*

Some approaches for user identification have used biometric solutions to associate touches with a persona. HandsDown (Schmidt et al., 2010a) performs user identification by analysing the hand's contours. Figure 2-12 (left) shows an example of the feedback provided by this system. Once a user is registered, the system provides access to personal data, associates objects with user's identity, and allows customisation of appearance, content or functionality. However, the approach did not offered a solution for a multiuser setting or to associate further touches with specific users.



Figure 2-12 User identification at the tabletop through biometrics. Left: HandsDown (Schmidt et al., 2010a). Right: IdLenses (Schmidt et al., 2010b).

<sup>1</sup> <http://www.microsoft.com/en-us/kinectforwindows/>



A more recent approach is MTi (Blažica et al., 2013). This consists of an algorithm that, similarly to HandsDown, identifies users using biometrics based on a number of features extracted from the touch points of user's fingers placed in certain order on the interactive surface. This work made this approach applicable to any kind of interactive tabletops regardless of the technology used to sense contact points. Neither system offered a solution to associate touches with identified users.

IdLenses (Schmidt et al., 2010b) is a similar system that identifies part of the contour of the hand in order to provide a personal interactive area on the tabletop surface through which the user can interact with the content (see Figure 2-12, right). However, this approach imposed usability problems since it does not allow for direct touch manipulation as it forces the user to place a second hand on the table for user identification purposes.

The majority of the touch-identification mechanisms presented in the section are prone to certain forms of inaccuracy or they are highly coupled to certain touch sensitive hardware. This makes them difficult to apply with other already available tabletop hardware. This motivated our development of a novel method to provide user differentiation and a further exploration to provide user identification by placing a personal device on the surface to pair each touch with a persona. This development goes beyond the aim of thesis. Therefore, it will be briefly discussed in Chapter 5 but more fully described in Appendix Section A.3.

### *User localisation*

This category includes interactive surfaces that are aware of each user's activity and location beyond the touch point area. Medusa (Annett et al., 2011) is a proximity-aware multi-touch tabletop that uses a network of 138 proximity sensors placed on the edges of the tabletop to detect user's location, arm direction, their hand being used, and associate touches to specific users and hands (Figure 2-13, left). Ballendat et al. (2010) explored ways to capture contextual information of users such as position, proximity, focus of attention and activity, to offer personalised format and content delivery according to the user's needs (Figure 2-13, right). Even though this approach is not strictly applicable to horizontal shared devices and it requires pieces of hardware to be worn by users all the time, it is still a key work that addresses shared devices awareness of users around them.

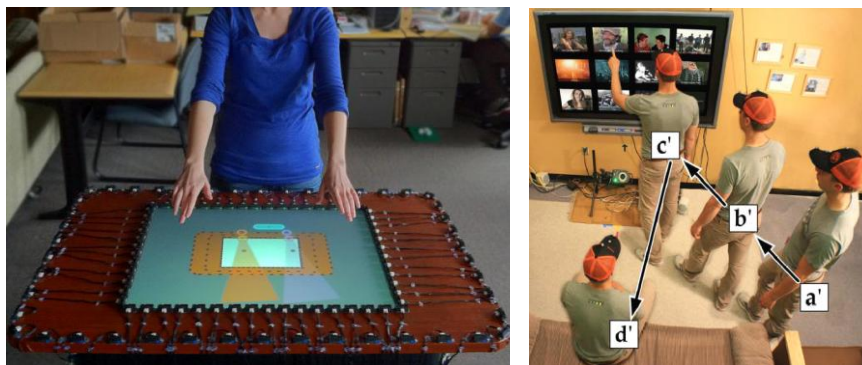


Figure 2-13 Systems that afford user localisation awareness. Left: Medusa (Annett et al., 2011). Right: Proxemics interactions (Ballendat et al., 2010).

Finally, there has been little work considering user's speech to provide insights about interaction at the tabletop or for collaboration analysis. One key study, conducted by Tse et al. (2007), proposed a multi-modal tabletop that provides both speech and gesture commands to interact with the system or to establish implicit communication with peers. Other examples have mostly been limited to recording audio traces that are further manually analysed (Falcao and Price, 2009; Fleck et al., 2009; Jermann et al., 2009). However, most of these approaches have relied on asking participants to wear small microphones or to be video-recorded. As a result, these are too intrusive for use in authentic classroom settings or to provide affordances for automatic speech analysis. One of the few exceptions is the Reflect Table (Bachour et al., 2010), a non-interactive table that mirrors the level of speech unobtrusively captured by a microphone array. This will be further described in Section 2.3.4.

### 2.3.3. Tabletop User Interfaces for Collaborative Learning

Several research projects have explored the use of interactive tabletops in learning contexts (Dillenbourg and Evans, 2011; Higgins et al., 2011; Kharrufa et al., 2010; Morris et al., 2005; Rick et al., 2009; Schneider et al., 2012; Stock et al., 2008). Our work was influenced by these preceding studies. One of these is the work done by Stock et al. (2008) who explored the affordances of tabletops to help students discuss a challenging topic in order to foster reconciliation of diverging perspectives, or to agree on the points of disagreement. Therefore, this is one of a few examples of tabletop systems that have taken advantage of touch identification to provide an interface aware of which student is performing each action for a learning scenario. The hardware used for this study was the Diamond Touch (Dietz and Leigh, 2001) which allowed them to design *collaborative gestures* that forced students to externalise their agreement in an explicit form. Notably it involved only dyads, each student with a different perspective of the reality, as they worked on a reconciliation activity.

Another key study was conducted by Morris et al. (2005). This evaluated the impact of making changes in the design of three learning applications in the domain of foreign language learning (to classify vocabulary words, to match phrases with images, and for poetry creation). This study is one of the first in the literature that addressed the problem of having one teacher for many students using tabletops. The authors investigated the importance for groups to receive feedback privately at the tabletop with and without the presence of an instructor. The study involved a preliminary analysis of hypotheses in a controlled setting, to then analyse the impact of the findings in a more authentic setting with less controlled conditions. This is one of the first pieces of research works included teachers at least for the evaluation of the designs.

Research by Fleck et al. (2009) highlighted the importance of analysing both the verbal communication and student's physical actions to facilitate collaborative learning at the tabletop. This work also was grounded on theories of CSCL in order to support the analysis of collaboration at the tabletop that may be incomplete if this evaluation is carried out from an HCI perspective only. The authors built on theories of construction of shared knowledge (Roschelle and Teasley, 1995) in a collaborative problem solving scenario. The Diamond Touch table was used with OurSpace, an application that allows children to design a plan of their own classroom (Figure 2-14). The study consisted of a deep qualitative analysis of verbal and physical student's interactions around the tabletop focusing on discovering the strategies used by children to coordinate their collaborative work. The authors analysed the transcribed conversations to describe the ways in which joint awareness is maintained aided by the interactive shared device.

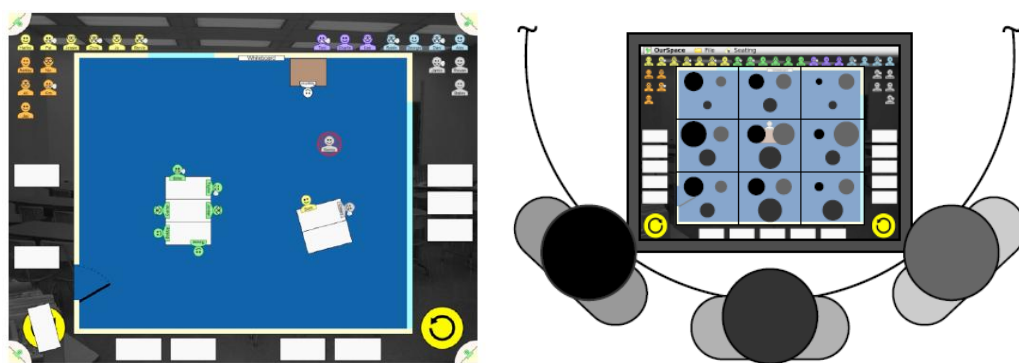


Figure 2-14 OurSpace: an application for collaborative design of spaces (Fleck et al., 2009; Rick et al., 2009).

Rick et al. (2009) conducted a more quantitative study using the same system to investigate indicators of collaboration that could potentially be automatically measured from students interactions. These indicators focused on evaluating the impact of touch restrictions and the position of children around the table on the strategies they followed to build their joint map. This work highlighted the importance of the design of the tabletop software, showing that this can make a strong impact on the way students coordinate their work.

Morgan and Butler (2009) identified a set of collaborative learning design issues for creating effective multi-touch technology to be used in the classroom. They proposed a theoretical approach for designing tabletop applications that encourage learning with high levels of collaboration, grounded on theories of collaborative learning, for example, Situated Cognition (Brown et al., 1996) which would be associated with the learner's authentic tasks in authentic contexts at the tabletop; Distributed Cognition (Cole and Engeström, 1993), if considering the group activities supported by the tabletop as a mediating artefact; and Constructivism (Vygotsky, 1978), which highlights the importance of the dialog and face-to-face communication, as shown in Figure 2-15. According to this layered approach, the designer of tabletop applications should consider the impact of the context of the learning activity, the affordances of the hardware for group work, and the collaborative interactions between students. The authors designed systems for storyboarding, concept mapping and building phonemic awareness between dyads (Butler et al., 2010) in order to provide examples of collaborative learning tools. Additionally, these studies were among the first that strongly argued that student's actions should be differentiated around the tabletop to provide a more effective experience and feedback. However, even though they proposed a possible solution, mostly based on software design (e.g. providing personal regions of interaction, establishing roles to limit student's actions or similar approaches), these were not implemented or evaluated in the classroom.

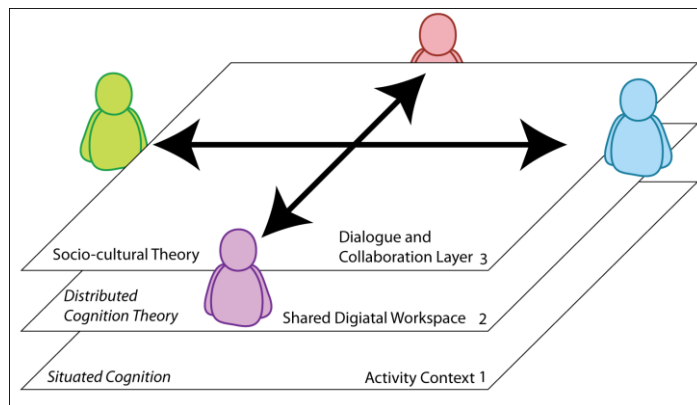


Figure 2-15 Representation of a theoretical approach proposed by Morgan and Butler (2009) for designing tabletop grounding on strong theories of collaborative learning.

We also build on the work by Kharrufa et al. (2010), who described an approach for designing tabletop applications based on theories of collaborative learning. This work focused on interaction techniques for digital tabletops; and the design and evaluation of a digital tabletop-based system called “Digital Mysteries”, that allows students to gather and organise key information about a given scenario in order to discuss and build a solution as a group. One important aspect of this work is that all student's actions were automatically recorded and associated with the student who performed the action. Students interacted through an electronic pen-based system. Thus, this allowed user differentiation. This information was used in *real-time* to mirror information to the students about the distribution of their contributions in the form of a simple pie chart.

However, the most important use of this information, from our perspective, is that the dataset was made available for research in this thesis. This was used to explore the feasibility of the application of data mining techniques and to discover student's collaborative strategies. The description of the approach and results are presented in Section 4.4. The student's data were also exploited through data visualisation techniques by Al-Qaraghuli et al. (2011). The discussion of this approach will be presented in the next section that focuses on analysing tabletop collaboration data.

Another important avenue of research has been done using the Tinker Table (Jermann et al., 2009). This system consists of an overhead “lamp” that includes a camera that tracks printed fiducial markers that can be placed on pieces of paper or physical tokens, and a projector, which provides visual feedback according to the position of these markers, to create an augmented reality table. The Tinker environment has also been used to provide basic tracking of fingers (Figure 2-16, right). However, it does not provide proper multi-touch input options. It has mostly been used to allow students to interact by moving, rotating, bringing in or taking out a number of learning

materials such as pieces of paper with certain shapes, paper sheets or physical miniaturised objects (Do-Lenh et al., 2009). The authors argue that the manipulation of tangible objects may enhance the way students interact with the tabletop environment and therefore facilitate the collaboration processes that invite exploration towards finding a better solution (Schneider et al., 2011).

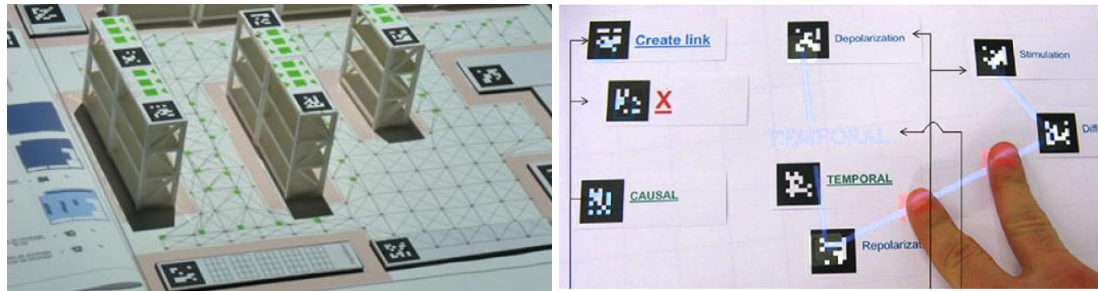


Figure 2-16 Tinker Table and Tinker Lamp: versatile tabletop environments that can track tangible objects, pieces of paper and some touch points (Dillenbourg and Evans, 2011).

The pay-off of using this kind of tangible objects is the restriction of content that can be shown and that the interaction with the system mostly depends on the movement of the physical tokens. The system was used for training basic logistics principles through a miniaturised workhouse simulation environment. The system visualises the movements of forklifts that move boxes from the tangible shelves to the trucks on the horizontal table. Then, students have to think about the optimal strategies to locate the shelves in order to optimise the use of resources (Figure 2-16, left). The same lamp has been used to help future carpenters acquire complex reasoning skills (Cuendet et al., 2011); to encourage school children to explore and understand basic principles of geometry and reflection (Bonnard et al., 2012); and to investigate collaboration behaviours of students building paper-based concept maps (Do-Lenh et al., 2009).

In other clearly related work, Schneider et al. (2012) presented a tabletop interface for fostering collaborative learning of phylogenetics. This study explored, not only the advantages of using tabletops to address students misconceptions, enhance collaborative learning, maintain mutual awareness and promote engagement, but also to create opportunities for reflection and encourage a sense of autonomy by working in small groups. As a product of this work, the authors suggested that tabletop applications for learning should provide support for reflection, engagement, and provision of feedback.

Even though there is a wide spectrum of research on tabletops for learning, as described in this section, the deployment and study of most of these tabletop systems in real and authentic settings is still missing. This is caused partly by the lack of useful realistic applications that can be integrated into the current teaching practices and authentic curricula. This can make the cost-benefit relationship a problem for most of educators.



Figure 2-17 GreenTouch: a multi-device learning system that includes tabletops to explore biological information that can be collected in the field (Valdes et al., 2012).



One of the most recent studies that aim to integrate tabletops in real tutorials was presented by Valdes et al. (2012). These authors described the design, implementation, and validation of the GreenTouch system, a collaborative environment that enables students to engage in an authentic activity in a biology subject in which interactive tabletops are used within a chain of activities, where students meet at the tabletop to explore information captured in the field using their mobile devices (Figure 2-17). Their system also offers a web application that has access to the same data that can be explored or captured through other devices.

More research projects that aim to bridge the gap between tabletop technologies and the classroom practice are presented in section 2.3.5 and our own classroom technology in Chapter 8.

### 2.3.4. Tabletop-supported Collaboration Data Analysis

This section discusses research work that has mostly focused on visualising, mirroring or analysing student's data that was captured manually or automatically from face-to-face environments. As could be observed in some of the studies described in the previous section, there is a growing interest on providing support, some type of adaptation or automated feedback to students, in-*real-time* or for further reflection, using the tabletops systems (Martín and Haya, 2010)

The Reflect table (Bachour et al., 2010) is one of such systems that aims to promote balanced discussions by mirroring the levels of speech of each participant. The system consists of a non-interactive tabletop with a small microphone array in the centre (Figure 2-18). This allows the system to determine the direction of the surrounding sound, therefore distinguishing the current speaker without requiring students to wear any attachable microphones. The tabletop contains a matrix of coloured LED's that turn on according to the amount of speech from each user, as detected by the microphone array.

The authors discovered that this system is somewhat effective in regulating egalitarian participation. Results showed that over-participators tend to reduce their participation but under-participators are not motivated to improve their contributions level, even when the mirroring information is provided. This demonstrates that showing information to the students, without a proper guidance (e.g. with more comprehensive feedback given by a teacher), does not necessarily lead to an improvement in collaboration or individual contributions. A follow up study using this environment (Roman et al., 2012) analysed, in more detail, the automatically captured verbal information, discovering patterns of verbal interaction that were indicative of presence of leaders, changes on behaviour between meetings and that groups may tend to regulate over time. The relevance of these studies for our work is in the analysis of modest speech data, without needing speech content analysis, in order to discover important indicators of group work, collaboration and balance.

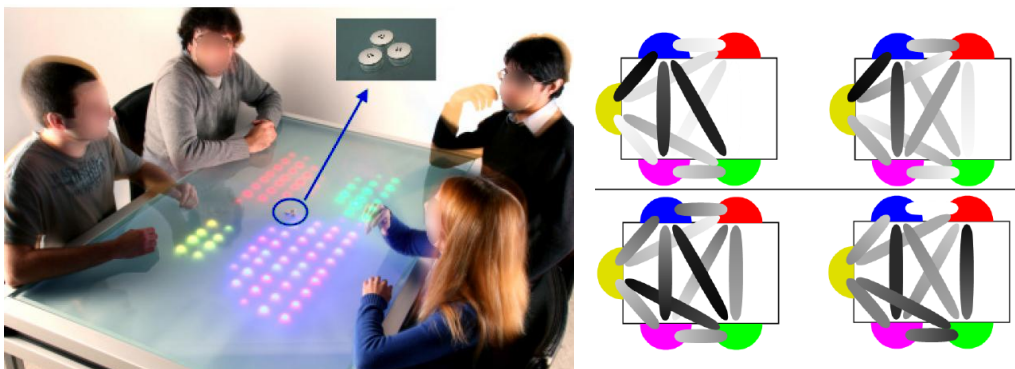


Figure 2-18 Reflect table: a non-interactive device that reflects amount of verbal participation (left) and speech patterns (right) in group meetings (Roman et al., 2012).

By contrast, VisTaco (Tang et al., 2010) is a visualisation tool that was developed to inspect patterns of touch interaction of groups working, in this case, on multiple tabletops located in

different rooms (Figure 2-19, left). This non-collocated environment allowed authors to differentiate user's touches without using tabletops that afford identification capabilities. However, the visualisation tool developed in this work was limited because it only showed the finger contact points on the interactive surface and the traces of these while moving from one point to another. Even though these *heatmaps* (like the one presented in Figure 2-19, right) can give some information about territoriality behaviours, it does not show much about the collaborative processes that occur above the tabletop. A similar approach was followed by Rick et al. (2009), who explored the impact of the spatial distribution of school kids around a tabletop on aspects such as collaboration and division of labour, by inspecting these heatmaps of touch points. The take away message from this work is that the very low level touch data does not provide much information about collaboration and work performance, but can still be useful to highlight some possible trends of usage of the interactive surface and spatial issues.

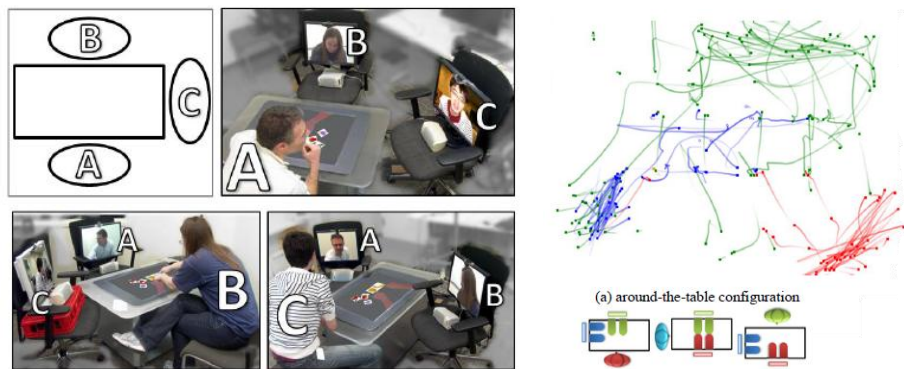


Figure 2-19 VisTaco: a system to visualise low level differentiated plots of touch input in a distributed multi-tabletop controlled setting (Tang et al., 2010)

Part of the work done by Jermann et al. (2009) also proposed interesting ways for exploiting students data from a collocated tabletop scenario. Using a larger version of the Tinker lamp (Figure 2-20, left), they ran small studies with students of logistics and captured information and observations about each learner speech and their actions. With these data they could produce visualisations, such as the one shown in Figure 2-20 (right), that they called *group's collabograms*. These give information about the amount of speech each student produced, directed to another particular learner, or to the whole group. Ideally, if this type of visualization can be automatically generated it would be very useful for the teacher to foster students reflection. However, this study mostly relied on observations and analysis of the speech recorded through individual wearable microphones. The latter makes the approach better suited to experimental lab settings, rather than an authentic classroom environment.

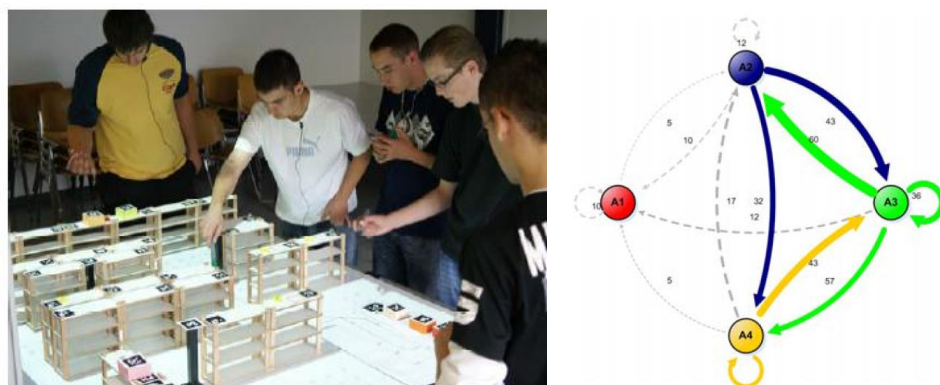


Figure 2-20 Analysing collaboration through a simulation-based logistics system. Left: Tinker Table system. Right: A collabogram representing learner's verbal interactions (Jermann et al., 2009)

Finally, a research project that is closely related to our work was presented by Al-Qaraghuli et al. (2011). Figure 2-21 shows one of the visualisations of student's data working collaboratively at

the tabletop using Kharrufa et al. (2010)'s Digital Mysteries. The hardware device used in this study could recognise student's input through a pen based system. These visualisations display the events that students performed in the timeline. There are three horizontal lines for each event type (vertical axis), corresponding to the three students working in each small group. This work points to roles of data captured by a tabletop system. However, it stopped short of a deep analysis of ways in which curated information might be made useful for the teacher or to identify key interesting patterns of student's collaboration. This work was partly inspired by our initial research to exploit sequential data to discover patterns of group collaboration at the tabletop, presented earlier in the same year (Martinez-Maldonado et al., 2011f), as described in Chapter 4.

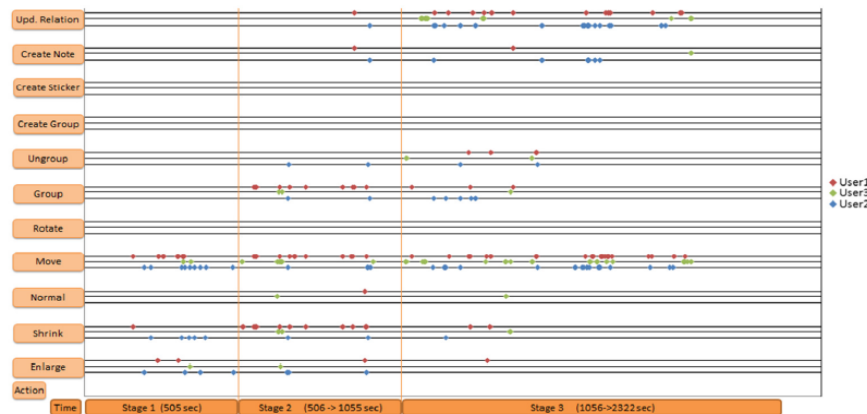


Figure 2-21 Visualisation of learner's actions proposed by Al-Qaraghuli (2011).

### 2.3.5. Multiple Tabletops in the Classroom

One of the most promising scenarios in which the data captured by the tabletops can directly help teachers is the deployment of multiple tabletops in the classroom. One of the first and most relevant projects on multi-tabletop environments is SynergyNet (AlAgha et al., 2010). This is a classroom with four multi-touch tabletops that was used to run experiments with elementary school students engaged in an extracurricular problem solving activity (called Mysteries). The teacher can visualise, interact with and control each group's tabletop screen from the teacher console. The work involved qualitative observations of video-recordings to study how tabletops can support collaborative learning interactions and the ways the teacher uses the system (Mercier et al., 2012). Teachers can monitor and directly interact with a specific group's tabletop. At the end of the activity, teachers can also use this tool to replay the process followed by certain groups to help students reflect about their collaborative interactions. However, the work was artificial in two respects: the task that students were asked to complete was outside their normal subjects and the teacher was not involved in the design of the class activity.



Figure 2-22 SynergyNet's multi-touch classroom (Higgins et al., 2011).

Another similar learning environment was presented by Do-Lenh (Do-Lenh, 2012). This consists of four non-multi-touch but tangible tables that can keep track of fiducial markers attached to objects located on a flat surface. The learning activity was based on a simulation training application for logistics. The system had different ways to help a teacher orchestrate the classroom. These were a wall display that shows task progress; controls for the teacher to compare two group's answers; and paper cards that a teacher could use to control individual tables. However, this work mostly focused on evaluating the usability of their tools rather than integrating the teacher into the activity design or linking the task to the regular curricula.

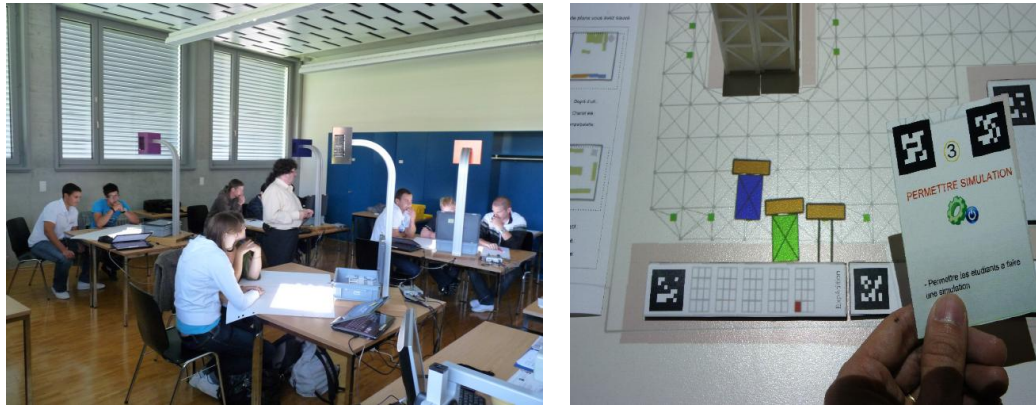


Figure 2-23 Do-Lenh's (2012) multi-tabletop classroom. Left: Multiple Tinker Lamp devices in the classroom. Right: Orchestration cards used by the teacher to trigger commands on individual tables.

In summary, these two previous approaches provided excellent background studies, but were not deployed in an authentic setting. This means that even when real students or teachers were involved in the studies, the tasks were not designed by the teacher and all sessions were experimental and not linked with authentic curricular activities. Neither of them addresses our key concerns of supporting a teacher in designing, orchestrating and reflecting on the design of an authentic activity as part of the curriculum. There was also limited automatic data capture. The information captured has mostly been targeted to researchers, designers or for in-class use only. Our work goes beyond such previous works by providing an approach to help teachers evaluate their classroom activities *design* in authentic tutorials using multiple interactive tabletops and orchestration tools. We also show that it is possible to pervasively capture rich classroom and student's data through the interactive tabletops. Then, these data can enhance the teacher's post-class *reflection* and *assessment* of the activity design and how it played out over delivered sessions.

A third multi-tabletop deployment was presented *after our own studies*. This approach integrated from 6 to 7 small SMART Tables<sup>1</sup> in a primary school to analyse observable behaviours of student's and teacher's interaction with the technology. Based on these, authors proposed a set of recommendations for designing multi-tabletop settings deployed in the classroom (Kharrufa et al., 2013a). The distinguishing factors of this study were primarily its scale and authenticity. The study was carried out for 6 weeks and students used the tabletops from 4 to 7 sessions and five different teachers were involved.

Figure 2-24 shows an example physical arrangement of the tabletops in the classroom. As mentioned by the authors (Kharrufa et al., 2013a), this work is complementary to ours because it extends single group study designs (which have been diverse and numerous, as it can be seen in Section 2.3.3) to highlight the many issues that arise when trying to be deployed in a real and non-experimental multi-tabletop classroom. The main difference of this work with ours is that it focuses on offering design recommendations based on observations of a large study case and on the key factors for effective *classroom orchestration* (Dillenbourg and Jermain, 2010). These were described in Section 2.2.3. The study was run using two tabletop applications adapted to the classroom: a small version of Digital Mysteries (Kharrufa et al., 2010) and a collaborative writing application. This study listed a set of important factors to take into account when deploying tabletops in the classroom. For

<sup>1</sup> <http://smarttech.com/table>



example, the authors identified some of the same principles that we propose in this thesis. This includes the importance of providing teachers with *visualisations of key indicators of the process* of each small group to enhance their awareness. Teachers who participated in those studies asked for such functionalities even though authors did not implemented any solution to address these. This work was in parallel our own. It highlighted challenges for engaging students and helping teachers achieve awareness of each group of students is progressing.



Figure 2-24 Related work deploying multiple tabletops in the classroom, posterior to the work reported in this thesis (Kharrufa et al., 2013a).

### 2.3.6. Section Summary

In this section we first discussed the affordances of interactive tabletops to support collaborative learning. The main conclusion is that tabletops provide promising opportunities to design activities that, if effectively planned and scaffolded, can foster collaboration and learning. There is no clear evidence that interactive tabletops themselves offer direct learning benefits. Rather, they provide a space for students to decide how to collaborate and potentially, to work more effectively. Then, we highlighted the affordances of tabletops to capture learner's actions. We also identified a lack of work on effective ways to capture learner's progress and identified tabletop actions. We presented key user interfaces that have been developed to aid collaborative learning and the little research work on exploiting the activity data at the tabletop. We finished with a review of the studies that have deployed tabletops in the classroom. The first two of these were mostly focused on evaluating experimental conditions or usability issues. A third multi-tabletop study, presented after the work contained in this thesis, provided some design guidelines from an HCI perspective.

## 2.4. Analytics and Data Mining of Collaborative Learning

There has been substantial progress in the development of technologies that enable learners to collaborate, mainly through networked systems (Jeong and Hmelo-Silver, 2010). Large amounts of data can be captured as a result of the interaction of students with these systems. Student's actions can be recorded at different levels, from video capture, that has mostly been manually analysed, to logging all the system events, which can be automatically analysed.

Student's data can be used for self-regulation (by students); for scaffolding, coaching and evaluation (by students and teachers); or for post-hoc analysis, design-based interventions, etc. (by researchers). One way that information can be presented to the actors is through visualisations of the key indicators so that they can take appropriate actions. Also, software agents can trigger automatic actions of regulation. By contrast, in face-to-face settings students commonly learn in the physical presence of an instructor who helps to guide the collaboration and in which the role of the technology is frequently not dominant.

The area of *analysis of indicators of collaborative learning* can be found as subsets of research in learning analytics (Siemens and Baker, 2012), EDM (Baker and Yacef, 2009) or analysis of

collaborative interactions (Harrer et al., 2009). A wide spectrum of techniques has been used to produce and visualise group indicators in a wide range of learning situations mediated by technology. Dimitracopoulou et al. (2006) presented a taxonomy of indicators that can be used to represent aspects of group interaction, for example, *collaboration intensity*, *participation rate* or *division of labour*. Some of these indicators, such as *quality of collaboration* or *common understanding*, are difficult to detect even through human judgement. Therefore they impose limitations in terms of what can be measured automatically.

This section describes two main types of studies on using analytics techniques to help understand collaboration processes. Under this umbrella, we first include a review of previous work on the use of visual representations or Open Learner Models (Bull and Kay, 2008) to graphically externalise student's collaborative data (Section 2.4.1). Secondly, we present the exploratory but significant work on the field of educational data mining and artificial intelligence that has addressed collaboration datasets and team work settings (Section 2.4).

### 2.4.1. Visualising Collaboration and Group Learner Models

There has been considerable work exploring the importance of group visualisations to externalise the activity of groups and, in some cases, to reveal relationships between observable patterns, the quality of the group work or trends in student's activity. Indeed, before analysing large data sets of logged user interaction with complex data mining techniques, it makes sense to check for coarse trends, using simple statistical or analytics techniques. Frequently, simple approaches can lead to find very insightful patterns or motivate subsequent data exploration with more complex artificial intelligence techniques (Witten and Frank, 2005).

Erickson et al. (1999) introduced the concept of social translucence systems that can help support computer-mediated communication by showing simple quantitative aspects of user participation. This approach builds on three properties (Erickson and Kellogg, 2000). The first property, *visibility*, refers to the notion that users can more easily drive their attention to socially significant information that is visually presented in the form of figures. The second, *awareness*, considers the impact of showing users aspects of their activity that can trigger modification of their actions and social rules. Lastly, *accountability* refers to the processes of self-regulation that can occur as a result of user's awareness of their own actions or those of others.



Figure 2-25 Sociograms representing group members participation. Left: representation of an active group. Right: representation of a group with poor interactions (Erickson, 2004).

These authors developed a visual representation of chat conversations to deploy their principles to foster knowledge management. Figure 2-25 shows one of the implementations called the social proxy. As a person chats more, the coloured dot that represents her moves towards the centre. If they are inactive for a time, their dot moves out. The figure shows one group with group members who focused on interacting in chat discussions (left) and another group in which users were disengaged from the conversation (right). The authors showed that, even simple visualisations of quantitative information of group work can give a sense of the level of the interaction, the amount of conversational activity, as well as indicating whether people are gathering or dispersing. Additionally, this graphical representation can help focus attention on the group as a whole, and the progress of its activity (Erickson and Kellogg, 2000).

Similarly, but more focused on educational setting, *sociograms*, like the one presented above in Figure 2-20, have been extensively used in the CSCL field to visualise learner interactions (Jermann et al., 2009). They have also been applied to represent the lines of communication within social

networks (Sundararajan, 2010). In addition, Janssen et al. (2007) explored the effects of visualisation of participation in groups of learners. They found that visual representations of activity mirrored to the group can be useful for encouraging coordination and regulation of the members. Donath (2002) went a step further by showing some qualitative aspects of user's *participation* in a visualisation of group activities that can facilitate the identification of dominant group members or possible patterns of interaction. Partly inspired by the sociograms and Donath's (2002) work, Kay et al. (2006) designed a set of visual representations of long term activity for an educational setting. Building on a model of small group teamwork they created a set of visualisations to identify anomalies in online team work by mirroring aspects such as participation, interaction between members and leadership. Figure 2-26 (left) shows a visualisation, *The Wattle tree*, which depicts a vertical timeline and a tree of events for each group member. Each of the elements (circles and spikes) in the visualisation shows the presence and size of each student's contribution to the group project. Figure 2-26 (right) shows other 2 visualisations called *Interaction networks* which show the interactions that occurred among group members. These can help a teacher compare groups or identify students who interact very little with other group members. The authors found that the succinct information provided by their visualisations correlated to useful aspects of group performance, and helped teachers and students enhance their awareness of the long term process followed to complete the group project.

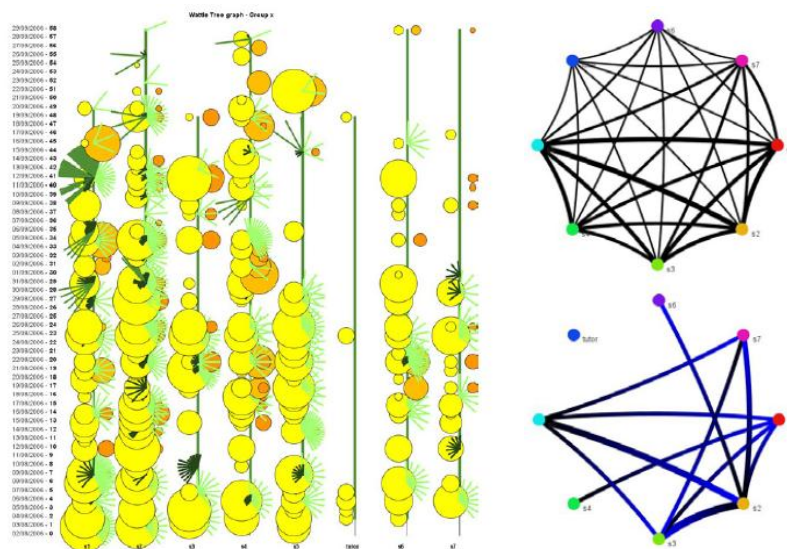


Figure 2-26 Visualisations of team work. Left: the Wattle tree. Right: Interaction networks of an egalitarian group (above) and an asymmetric group (below) (Kay et al., 2006).

A third key related visualisation showed student's collaborative data as the *Narcissus* interface (Upton and Kay, 2009). *Narcissus* (see Figure 2-26) introduced a scrutable visualisation that at first glance appears similar to *The Wattle tree* (see Figure 2-26, right) presenting broad information about each student actions through vertical timelines. However, this interface enables students to navigate through the visualisation to see the detailed evidence that contributed to each part of the visualised group actions (Upton and Kay, 2009). Another key contribution of this project was the deployment of the visualisation tool within a real learning environment used at an authentic university course where it improved group success. This highlights the importance of showing end users (students and teachers) key information of different levels of detail to promote reflection and awareness of the group processes.

Some of the most prominent work on visualising individual student's data or networked collaborative settings can be very inspiring and extended to face-to-face collaborative environments. These include research work on Open Learner Models (Bull and Kay, 2007; Bull and Vatrappu, 2011) and analysis of collaborative interactions (Soller et al., 2005). Open Learner Models (OLM's) are representations of certain aspects of learner's knowledge, activity or performance that can be captured by the learning systems and that are shown to the users or their teachers. There are many different ways to present an OLM for example, through visualisations, graphs, bars or even succinct information (Bull and Kay, 2007). Recently, there has been a growing interest in ways to present this

information to the teacher in the form of teacher dashboards that can be accessible in and out the classroom (Bull et al., 2012). This thesis partly addresses this by offering key visual information to the teacher for in-class support or for after-class deeper analysis.

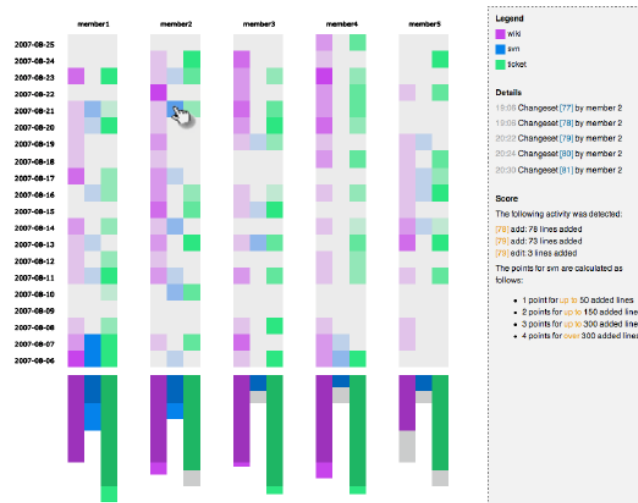


Figure 2-27 *Narcissus* system. An scrutable tool to navigate through the learner models of team work and participation (Upton and Kay, 2009).

Soller et al. (2005)'s distinguished between two approaches for designing support systems for collaborative learning. The first consists of capturing data about student's interaction, and showing some visualisation of this information to the user, possibly with additional information of an ideal group. In this case, the user (students or teachers) are free to interpret the visualisations and decide what further actions they should take to enhance the collaborative process. This is the level of information that this section is focused on. The second approach consists of the generation of a model of student's interaction that the learning system can use to make decisions on how to moderate the group or which suggestions to offer to students or the teacher. In this case, the analysis of the data is hidden from the user's awareness and control.

## 2.4.2. Data Mining of Group Interactions

The use of Data Mining or Artificial Intelligence techniques in collaborative learning environments has proven successful in gaining insights into the interactions within groups that lead to high-quality results in terms of collaboration (Anaya and Boticario, 2011; D'Mello et al., 2011), conflict resolution (Prata et al., 2009), teamwork (Perera et al., 2009) and correctness of the task solution (Talavera and Gaudioso, 2004). Initial research proposals that have addressed the study of the collaborative learning processes applying data mining techniques include the work done by Soller et al. (2002), who used Hidden-Markov Models to identify the episodes when students share knowledge at a constrained and scaffolded networked system. Other key work was performed by Talavera & Gaudioso (2004) who formally pioneered the intersection between CSCL and EDM to study student's collaborative interactions in order to find patterns of behaviour. These authors presented a case in which they applied a clustering technique on e-learning data to build student profiles based on a set of features associated with learner's interactions with the system. These include, for example entries to a forum, access logs to course materials, added bookmarks or messages sent to their peers. Even when their approach did not consider groups of students as a whole, it aimed to present profiles of student's behaviours to the teacher.

Building on this previous work, Anaya & Boticario proposed both supervised classification (Anaya and Boticario, 2011) and unsupervised clustering (Anaya and Boticario, 2009) techniques for grouping students according to their level of collaboration, assigning a value to each student to facilitate comparison of student's behaviour. Similarly to the approach followed by Talavera & Gaudioso (2004), these authors extracted a set of features from logged student's interactions



through a forum-like learning environment. However, they conducted a larger and longer study at an authentic distance learning university, and compared the results of the data mining methods with empirical assessments of the quality of student's contributions. The results of this project proved that data mining methods can reveal representative indicators and help learners or their teachers to improve collaboration or their learning activities.

Additionally, some researchers have tackled the analysis of collaboration using sequential pattern extraction. One important study on online learning data was performed by Perera et al. (2009) who explored the usage of sequence pattern mining and clustering to find trends of interaction associated with effective group-work behaviours in the context of a software development tool. Differently from the previous approaches that used clustering techniques, in this study the authors clustered both, groups and learners, according to quantitative indicators of collaboration. However, one of the main novelties of their work was the introduction of the use of alphabets to represent sequential actions that can be performed by more than one learner on different learning artefacts. This allows sequential mining algorithms to discover frequent patterns of interaction including information from multiple users in the data mining process itself. The patterns found can then be associated with behaviours that may distinguish strong from weak groups and help teachers to identify groups with possible problems in early stages of the collaborative work.

Clustering and sequence mining have proved effective in discovering patterns from collaboration datasets. However, they are not been the only techniques used to model indicators of collaboration. Duque & Bravo (2007) presented a fuzzy model that generates rules to classify the different forms of collaboration that leads to solutions of a certain quality. Prata et al. (2009) presented an automated detector of the nature of the utterances written at a math online system in terms of collaboration focusing on the identification of conflict between peers. Other techniques have also been used to mine sequential patterns from collaborative data including Hidden Markov Models (Soller and Lesgold, 2007), Social Network Analysis (Casillas and Daradoumis, 2009) and Process Mining (Reimann et al., 2009).

Most of these previous examples have focused on studying collaboration supported by online learning systems, for example online chat sessions, forums, wikis and intelligent tutoring systems. In these learning contexts most of the recorded communication is mediated by the system, making it easier to automatically log students actions compared with face-to-face environments. There is no previous work analysing the fine-grained interweaving of student's speech and touch activity when working at face-to-face shared devices using data mining techniques.

### 2.4.3. Section Summary

This section presented the emerging research trends in the intersection between CSCL and the automatic analysis of student's interaction data. We presented work on data visualisation that has been conducted from different perspectives (CSCL, user modelling and EDM). Then we reviewed the little research work on Educational Data Mining analysing collaborative learning environments. Although most of the research work presented in this section has addressed networked collaborative systems, the studies presented in this thesis build on some key principles presented in these projects. This thesis contributes to the development of visualisations, teacher's dashboards, and the application of a variety of data mining techniques in face-to-face collaboration data.

## 2.5. Learning Tool: Tabletop Concept Mapping

*Concept mapping* is an important educational technique, created by Joseph Novak (Novak, 1990). It provides an excellent means for a learner to externalise knowledge and build meaningful understanding about almost any domain. Moreover, concept maps are metacognitive tools that can foster the development of strategies for organising knowledge and facilitating communication of understanding (Novak and Cañas, 2008). In its beginnings, concept mapping originated in a research program to promote school children's understanding of important concepts in science (Novak,

1995). Then the technique was adopted by school programs, out of the research umbrella, and it started being used for a number of purposes such as helping teachers plan instructional materials and to evaluate students; aiding learners in representing their ideas; or helping groups of students share their individual perspectives.

Nowadays, concept mapping has been used in a number of school programs focused on a wide range of learning areas such as natural sciences, physics, social sciences, management or for resolution of cases and conflicts (Novak and Cañas, 2008). The technique has also been used in a number of areas in industry, business, public administration, national departments in a few countries and, *unfortunately*, even for military training (Cañas et al., 2003; Lawless et al., 1998; Novak and Cañas, 2008). Overall, the concept mapping technique is currently being widely used in a number of fields and for different purposes; it is also backed up by a strong international community of research and practice that has proved the effectiveness of the technique to support meaningful understanding (Cañas and Novak, 2008).

Concept maps are directed graphs in which the nodes represent the concepts of the domain. These are defined as perceived regularities in events or objects of a domain (Novak and Cañas, 2008). For example: *plants*, seeds or *stems*. The relationships or edges between the nodes are called propositions or principles. Propositions are indicated by a labelled line linking two concepts. The direction of the arrow indicates the reading direction, generating a meaningful statement between the pair of concepts and a linking phrase. The arrangement of the concepts in a concept map is very important. The arrangement that was originally proposed by Joseph Novak was a vertical hierarchical layout, with the most general concepts at the top, more specialised ones lower and similar concepts at the same level and close to each other. However, other arrangements can be used to represent chained processes, cycles or concentric hierarchical representations (Nousiainen and Koponen, 2010). The propositions are the key elements of the concept maps because each one shows the learner's conception of the relationship between a pair of concepts. Another important characteristic of concept maps is the inclusion of *crosslinks*; these make explicit relationships between concepts in different regions or domains within the same concept map.

An example of a concept map is shown in Figure 2-28, where the most general concept is *Plants* and this is in three propositions, *Plants have Roots*, *Plants have Leaves*, *Plants have Stems*, and the concepts *Roots*, *Leaves* and *Stems* are less general than *Plants* and at a similar generality level to each other. Examples of *crosslinks* in this map are the propositions *Flowers produce Seeds* and *Seeds store Food*, which create an association between the sub-domains of *Leaves* and *Stems*.

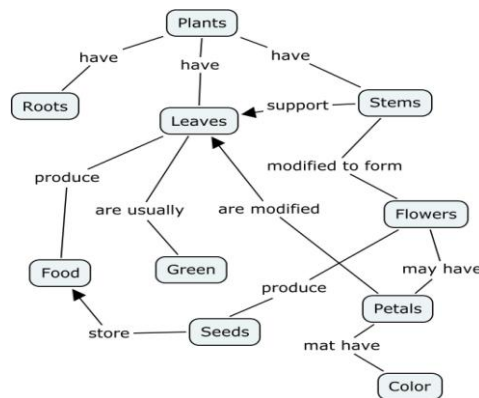


Figure 2-28 Example of concept map built with Cmap-Tools from (Novak and Cañas, 2008).

Concept mapping can be a cognitively demanding task. This means that one valuable approach for making use of the tabletop for concept mapping may involve a preliminary stage in which students focus on building a concept map of their understanding in private. Then, they can come to discuss their individual perspectives with other students to build a common map, identifying the similarities and discussing the differences between their perspectives. This might mean that one person changes their mind, altering their own map. At other times, learners may not be able to agree. For example, in a biology task, one student's map may have the proposition "a whale is a

mammal" while another student may have the proposition "a whale is a fish". One might convince the other to change or they may agree to disagree.

This section is organised as follows: first, it describes the benefits of collaborative concept mapping, and then, it presents a review of the current implementations of concept mapping applications deployed in interactive tabletops.

### 2.5.1. Collaborative Concept Mapping

Strong results indicate that concept mapping combined with cooperative learning can help students integrate new information with previous theoretical knowledge (Preszler, 2004) and make tacit and private knowledge public (Cañas and Novak, 2008). In this context, concept maps can be regarded as artefacts that model part of a domain of knowledge as perceived by the creators through the production of meaningful connections between the concepts involved. Novak's research (Novak and Cañas, 2008) has also indicated that building concept maps in a collaborative environment leads to greater learning and superior maps. The concept maps created by two different learners about the same topic can be either very different or, at least, have some differences in their structure and content. Thus, this creates the opportunity for using concept maps to facilitate collaborative learning, offering students the opportunity to discuss ideas, present knowledge from multiple angles, identify misunderstandings, reach agreement, or agree to disagree (Chaka, 2010; Gao et al., 2007; Novak, 1995; Stahl, 2006). Collaborative concept mapping also allows students to see other's concept maps to easily highlight the commonalities, their disagreements or to find possible misunderstandings.

The collaborative co-construction of concept maps may be conducted in different forms. Students can work face-to-face or at a distance through a computer-mediated communication system, and may be synchronous or asynchronous. As a result, currently there is a number of computer-based concept mapping tools that provide support in different forms. There are tools that provide support to teachers to facilitate the revision and assessment of concept maps, to students to be aware of other student's concept maps or changes to their group map, or tools that provide hints to students to improve their own concept maps by comparing them to other expert maps or using simple recommendation methods.

Next, we present three examples of computer-supported concept mapping tools that offer different ways to enhance learner's awareness and the quality of their concept maps. These include a concept mapping tool that coaches students in *real-time*, a tool that mirrors student's actions to promote self-regulation, and a system that allows students to collaborate and, at the same time, compare their individual maps with their peers.

The first example application that supports concept mapping is the Verified Concept Mapper, VCM, (Cimolino et al., 2004), which gives feedback on the maps, inviting learners to reflect on parts that may be incorrect as well as omissions. VCM provides support for teachers in creating concept-mapping tasks intended to capture the student's personal ontology of a small domain. The key feature proposed by this system is that it can automatically verify student's intentions when adding elements to the concept map that are then used to infer their understanding and possible misconceptions. The system proved effective in aiding the teacher to help the student to check for careless errors and focus on the key propositions that may reflect misconceptions.

Figure 2-29 shows the students interface that can be used to both build a concept map and request feedback by comparing the solution with the teacher's intended map. A secondary aim of this project was to build on principles of *student modelling* for VCM to show the student only the information that can be inferred from their individual model. In this way, the teacher can decide which carefully chosen parts of the intended map are provided to the student. VCM does not provide support for collaboration but it still is a good example of an effective way in which the information that is obtained from student's concept maps, can be used to generate a user model and provide adapted information and support for both teachers and students.

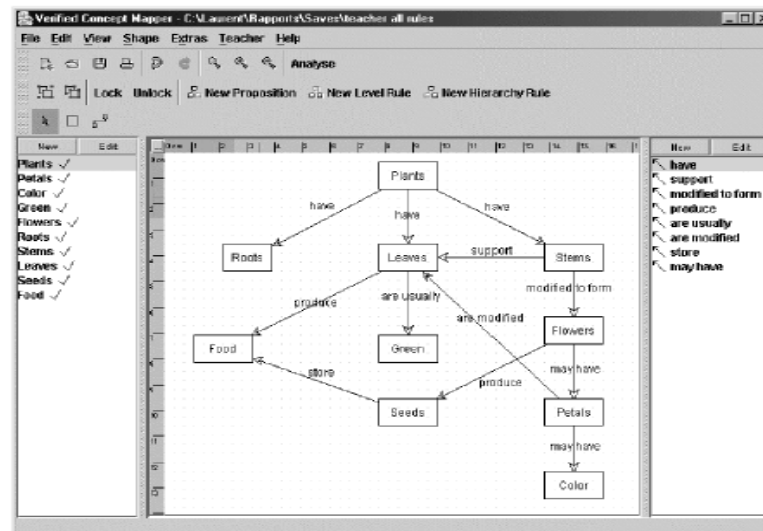


Figure 2-29 Verified Concept Mapper, VCM (Cimolino et al., 2004)

Another similar approach is followed by the Betty's Brain system (Leelawong and Biswas, 2008). Through this system the learner can create a form of executable concept map with the purpose of teaching a virtual agent (Betty) about the subject matter (see Figure 2-30). The principle behind this approach is similar to the one that promotes learning in collaboration settings: the externalisation of student's understanding to others. By externalising their own understanding to others, students have to reflect and articulate their knowledge.

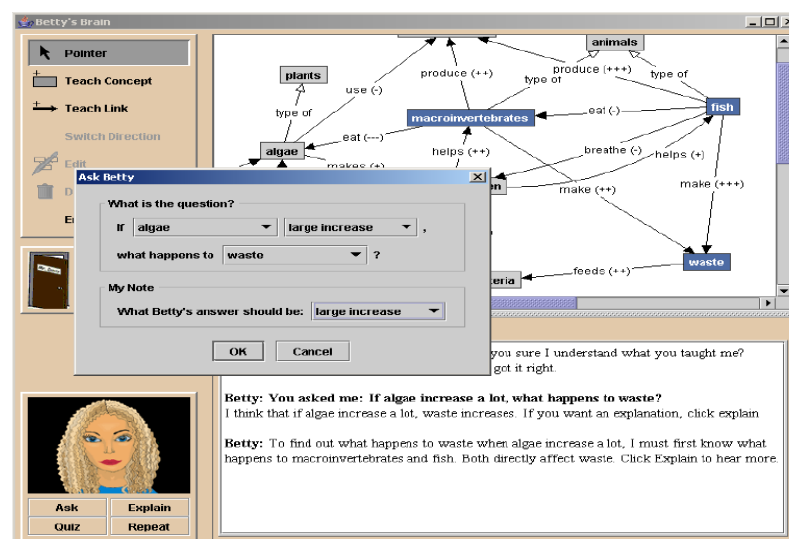


Figure 2-30 Betty's Brain user interface (Leelawong and Biswas, 2008).

Betty's Brain system also works as a mirror by repeating the propositions created by learners and provide the feeling that students are helping or teaching the agent. This was shown to promote metacognition as learners reflect on their own externalised knowledge model. Remarkably, this system has served to investigate patterns of student's interaction using artificial intelligence techniques, such as using hidden Markov models, to mine students behaviour models (Jeong and Biswas, 2008), or sequence pattern mining to discover the actions that differentiate high from low achieving students (Kinnebrew and Biswas, 2012). In this way, this work shows that the concept mapping technique can be a rich source of information about learner's understanding and possible misconceptions that can be exploited to feed effective metacognitive tools.

The third example is a collaborative mapping system (Engelmann and Hesse, 2010) that builds on the principle that the collaborative learning process can be enhanced by giving students the

opportunity to compare their perspectives (Tifi and Lombardi, 2008). Engelmann & Hesse's study (2010) specifically explores the impact of providing group members access to the knowledge representations and the resources of their peers while they build a collaborative concept map. Their concept mapping system offered a networked interface that allowed co-construction of the group map while having access to either each student's individual map previously build in private or the individual maps build by all the group members (see this interface in Figure 2-31). The authors compared groups of students who used this interface against those using a simpler interface that did not provide access to other's concept maps. Results showed that groups that were provided with other's concept maps acquired more knowledge about other's knowledge and then worked more effectively on the problem. This work showed that allowing students to visually represent their individual perspectives in private to then share them with their group to build an agreed solution can lead to improved collaboration and learning.

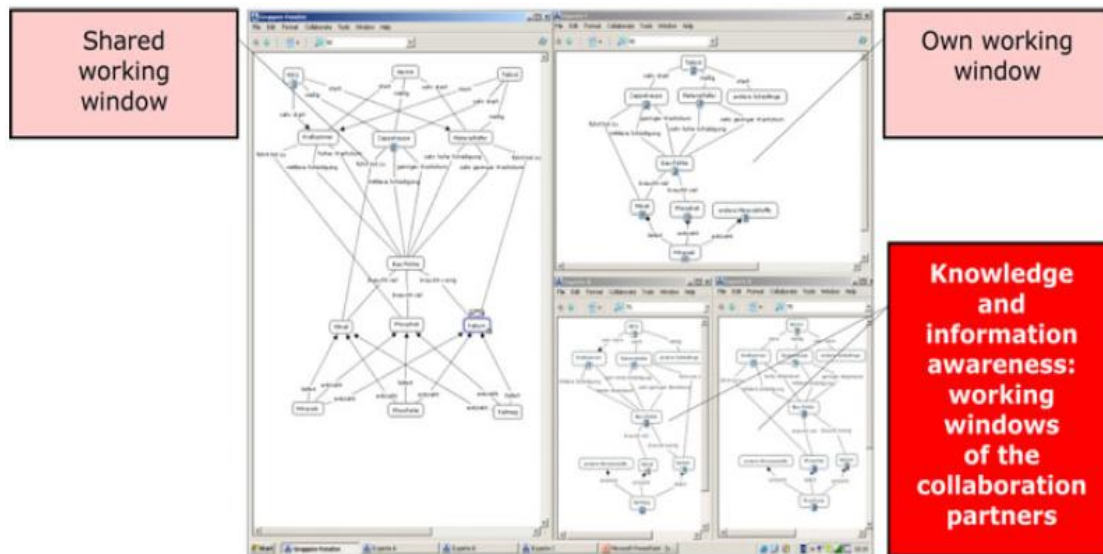


Figure 2-31 User interface that permits both the collaborative co-construction of a group concept map and the exploration of collaborator's individual maps (Engelmann and Hesse, 2010).

The next section describes concept mapping applications that have been deployed on interactive tabletops to allow users to create big format concept maps, mainly for collaboration.

### 2.5.2. Tabletop Concept Mapping

A number of researchers have explored the suitability of concept mapping for interactive tabletop environments. One of the first of these corresponds to the work done by Baraldi et al. (2006) who built a system that uses concept maps to navigate through wiki's content (see Figure 2-32).

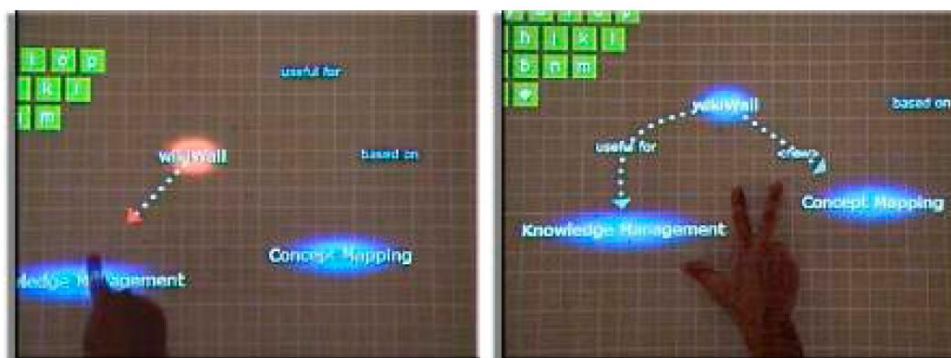


Figure 2-32 A concept mapping application to explore wiki content (Baraldi et al., 2006).

A wiki is usually used as a repository for knowledge elements that can be edited online by a number of users. As tabletops may support collocated work, the authors proposed that one of their possible uses is to synchronise the concept map and the wiki to allow users to build knowledge in a distributed form (through the classic wiki web interface) and face to face. This research work proposed the principles to build the gesture system for touch interaction and the interconnectivity infrastructure to access a central repository through a number of services and devices (web interface, tabletop, handheld devices). However, the system was not evaluated in an actual collaborative context.

Buisine et. al. (2007) presented an interactive tabletop system to support group creativity through the construction of mind-maps called Tabletop Mind-Mapping (TMM). The contribution of this work is that, although the system was not strictly a concept mapping tool, the design of the application considered the orientation of the content and text to allow all students around it to read the parts of the map that are closer to their position (Figure 2-33).

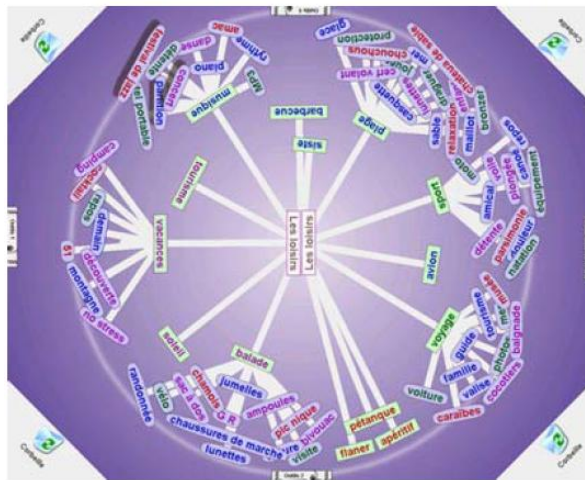


Figure 2-33 Example artefact created with the Tabletop Mind-Mapping (Buisine et al., 2007).

Tanenbaum et al. (2009) introduced a tabletop system that provided support to students to create a concept map through the use of tangible objects on the interactive tabletop (Figure 2-34). This system was limited to one user so the validation of the use of the interactive tabletop for discussion and collaboration was restricted to this use.



Figure 2-34 Exploration of tangibles to create concept maps individually (Tanenbaum and Antle, 2009).

Do-Lenh et al. (2009) performed the first study that compared the benefits of using an interactive tabletop for collaborative concept mapping with the use of a personal computer shared by the group members. Results were negative for the interactive tabletop as the authors did not find significant differences between concept mapping at the tabletop and sharing a conventional desktop computer. Indeed, they found that the groups sharing the desktop computer showed healthier



collaboration dynamics such as discussion and negotiation. However, the comparison was not entirely fair because sharing one desktop computer means that one mouse and one keyboard must be shared. Therefore, there is a restriction that does not exist at an interactive tabletop, in which all students have the same opportunities of interaction. Figure 2-35 shows the setting for the interactive tabletop condition using a version of the TinkerLamp introduced in Section 2.3.3, that was able, for this study, to keep track of pieces of paper and some touches.

Later, Oppl et al. (2011) looked for advantages of concept mapping aided by a tangible interactive tabletop. They presented an interface called Tabletop Concept Mapping (TCM) designed to aid cooperative learning activities and the development of a common understanding by representing the key concepts of the subject matter with physical objects (Figure 2-36). They compared the tabletop tool with a traditional screen-based system. They found that concept mapping at the tabletop offers student's equal opportunities of participation to share their individual understandings and therefore this helps students to build better and richer collaborative maps, compared with other mediums.

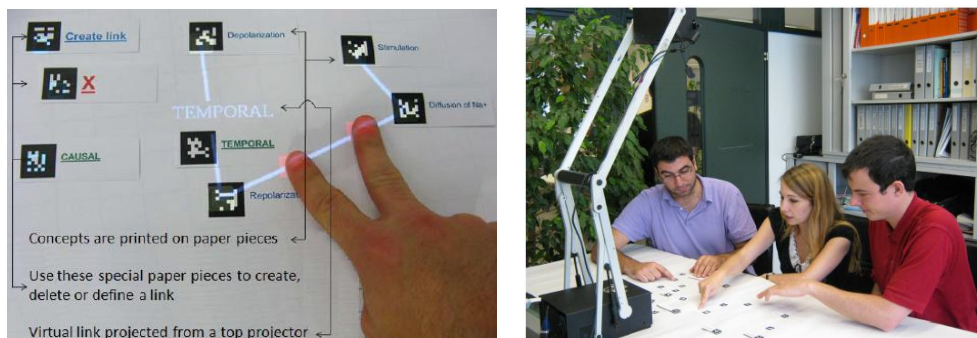


Figure 2-35 Paper-based concept mapping that allows students for more equalitarian participation when compared with sharing a personal computer (Do-Lenh et al., 2009).

If these results are compared Do-Lenh et al.'s (2009) and the other studies presented in this section we can see that the concept mapping technique has claimed tabletop software designer's attention. Tabletops offer certain affordances that do not necessarily ensure students collaborate better or worse, compared with other pieces or hardware. However, they offer a promising setting in which students can decide how to work and at the same time have access to the resources that the digital world can offer. This also holds for tabletop concept mapping.

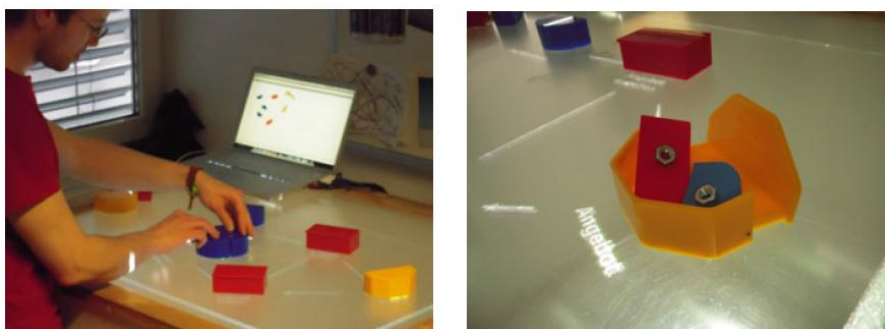


Figure 2-36 Tabletop Concept Mapping (TCM) using tangible objects (Oppl and Stary, 2011).

### 2.5.3. Section Summary

This section introduced the theories and principles behind the concept mapping technique. The relevance of this technique for this thesis is that most of the studies were carried out using our own tabletop concept mapping tool. This will be described in Chapter 5. The aim of this section is to highlight the importance of this technique that is, if not perfectly generalisable, certainly widely used in a number of areas of application, from educational settings to industry. The principles that the

concept mapping technique builds upon can also provide key insights about the student's understanding and the quality of their work.

## 2.6. Open Issues

The literature review presented in this chapter offers an overview of the state of the art of the interdisciplinary background context this thesis builds upon. The studies presented in this thesis together provide different contributions to the open issues that can be identified in each of the fields involved: Tabletops in Education from a CSCL perspective (Dillenbourg and Evans, 2011), Educational Data Mining (Baker and Yacef, 2009), CSCL in general (Jeong and Hmelo-Silver, 2010) and research on tabletop applications (Müller-Tomfelde and Fjeld, 2012). Most of the open questions in this context lay at the intersection of two or three fields or sub-disciplines.

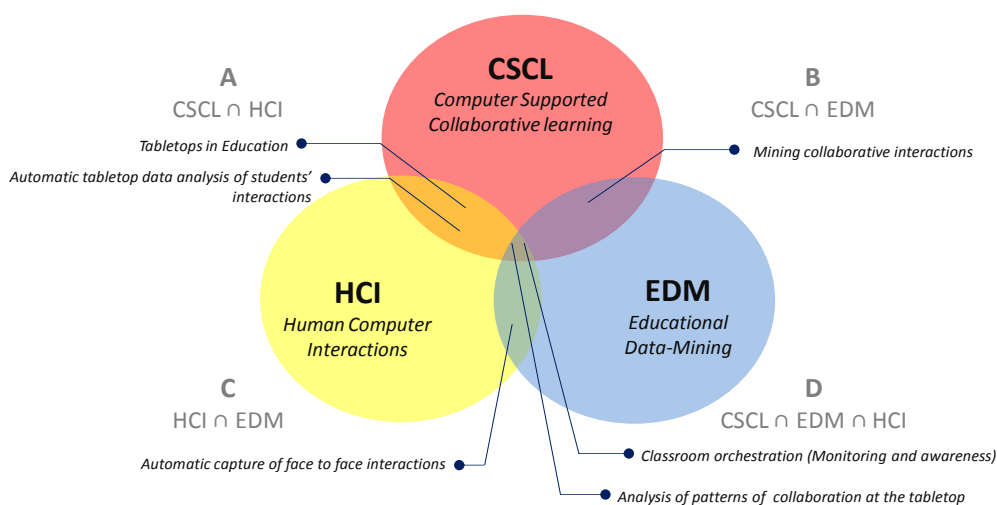


Figure 2-37 Open issues in the intersection of the fields involved in the thesis.

Figure 2-37 illustrates the intersection between HCI, CSCL and EDM fields, and the open issues identified from the literature survey presented in this chapter and a selection of meta-reviews written by experts in each field (Baker and Yacef, 2009; Dillenbourg and Evans, 2011; Dillenbourg and Jermann, 2010; Jeong and Hmelo-Silver, 2010; Müller-Tomfelde and Fjeld, 2012). The open issues can be grouped as follows:

*Issue A: CSCL and Interactive tabletops (HCI).*

Interactive tabletops have been a focus of research in the HCI community for more than two decades (Müller-Tomfelde and Fjeld, 2010). As described above in section 2.3.1, the unconstrained display orientation of this shared device allows users to interact through a rich digital environment with egalitarian access and maintaining face-to-face communication with their peers. These factors make it attractive for CSCL researchers to investigate the affordances of interactive tabletops in education (Dillenbourg and Evans, 2011). However, **even though interactive tabletops are novel, original, and exciting, the technology itself does not provide a radical change in learning or teaching.** The open issue in this regard is in finding the ways in which tabletops can be successfully integrated in real and authentic collaborative learning environments. This challenge is two folded. It requires a strong design of effective tabletop interfaces (taking account of usability issues that may affect student's interactions from an HCI perspective) but also this design cannot be unaware of the principles from CSCL to support collaboration effectively (CSCL oriented design). This emerging issue that is at the intersection between these two fields has not yet been deeply explored (Rick et al., 2013). A secondary open issue we address has been identified by Jeong et al. (2010) who reported there has been **little attention in CSCL research methodologies and studies targeting face-to-face collaborative settings and the little work done on developing automatic approaches to analyse these interactions.** According to that report, only 36% of the CSCL studies examined face-to-face



collaboration in the period 2005-2007. The data analysis in this kind of settings has traditionally relied on video and audio non-automatic coding, making it very difficult for teachers to get a direct benefit from the data collection and analysis in real classrooms.

*Issue B: EDM and CSCL.*

One open issue is the **modest amount of literature on the analysis of student's collaboration data using either artificial intelligence or data mining techniques**. Educational Data Mining is an emerging field that has mostly focused on discover patterns of interaction between individual students and learning systems (Baker and Yacef, 2009). However, there are some key projects, based on networked and online learning systems that have tackled collaborative learning problems. **The topic has been gaining formal interest in the community in recent years** (Kumar and Kim, 2013), focusing on providing intelligent support for group learning in the form of visualisations, teacher's dashboards, data mining, learner modelling and tutoring systems. These were reviewed in Section 2.4.2 of this chapter.

*Issue C: EDM and Interactive Tabletops (HCI).*

According to Müller-Tomfelde & Fjeld (2010), the trend in the adoption of interactive tabletop systems points to an increased use of them in a wide range of areas. Other trends in tabletops research and application include the development of new unobtrusive ways to distinguish concurrent input from multiple users and the enhancement of their context awareness. The current state of these affordances was discussed in Section 2.3.2. **If input differentiation can be provided then it would be possible to apply analytics and educational data mining techniques on student data captured through the interactive tabletops**. This can help discover patterns of interaction to better understand student's behaviours, similarly to approaches already used for networked learning systems.

*Issue D: CSCL, HCI and EDM.*

In this chapter we reviewed previous work on interactive tabletops from different perspectives including: learning applications (Sections 2.3.1 and 2.3.3), their affordances to capture student's data (Section 2.3.2) and implementations in the classroom (Section 2.3.5). The open issues this thesis tackled include the **lack of authentic deployments of tabletop technologies in the classroom for real activities linked with the ordinary curricula and the analysis of student's data that can be automatically captured and processed to support collaboration**. Under the umbrella of *classroom orchestration* (Section 2.2.3) we also identified that other researchers focused on the development of tools to enhance classroom control over multiple tabletops (and other technology present in the classroom), but not much was done in regard to supporting teachers to enhance their classroom awareness by providing monitoring and reflection tools. This is a key issue that this thesis addresses by **proposing means to show the teacher different aspects of collaboration from student's data**.

## 2.7. Chapter Summary

This chapter corresponds to the *informational phase* (see Section 1.5) of the engineering method that our approach follows to address the research questions (Section 1.1) of this thesis. This literature survey described the principles of CSCL that are important for our research. These include the theory of Group Cognition, principles on Classroom Orchestration, Interaction Analysis and current approaches to capture face-to-face student's interactions. Then, Section 2.3 presented a detailed review of the current state of tabletops technologies used for collaboration and learning. We described the affordances and limitations of tabletops to facilitate collaboration, the current trends to provide user differentiation and a number of collaborative learning applications. Section 2.4 described different ways in which it is possible to exploit collaboration data to produce visualisations and for artificial intelligence techniques. The smaller size of this section reflects the limited current state in exploiting and providing automated support to groups of students, especially when they are working face to face. Section 2.5 described the theory behind the learning tool that is

mostly used for this thesis: the concept mapping technique. We additionally review non-tabletop applications that are key in the formulation of our approach since they provide different ways of support to enhance student's performance. Finally, Section 2.6 presented a summary of the open issues that are addressed in this thesis in light of the review of related literature.

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## Chapter 3: Conceptual Framework

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*"There is nothing more practical than a good theory."  
– Kurt Lewin*

**Summary:** This chapter presents the conceptual framework of this thesis. This includes a full description of the learning situation that is addressed: a tabletop-based learning environment that can be implemented as a single tabletop where learners come to build a joint solution, or as multiple tabletops in the classroom that a teacher uses to design, plan, implement and assess authentic small group activities. This chapter provides details of the proposed student's data-driven conceptual framework which includes one Theoretical Foundation (TF) and three operational modules: the Data Capture Foundation (DCF), the Data Analytics Foundation (DAF) and the Data Presentation Foundation (DPF).

### 3.1. Introduction

The search to improve learning and productivity in the classroom by introducing new technologies has delivered very modest benefits to teaching practice, effectiveness of instruction or quality of productive learning from student's perspective (Cuban, 1986; Fabos, 2001). For example, this includes the high expectations and promises associated with the introduction of technologies such as radio, films, instructional television, or various kinds of computing tools, in educational environments (Cuban et al., 2001). As we stated in our literature review (Chapter 2), the introduction of interactive tabletops for learning is not very different compared with other technologies. Dillenbourg and Evans (2011) described this in terms of the tendency of *over-generalising* the possible benefits of tabletop devices for many educational challenges, and the *over-expectation* of their affordances. Table 3-1 presents an overview of the positive and negative affordances of interactive tabletops that can either motivate or limit the adoption of these devices for learning.

Having these affordances acknowledged, we set the main aim of this thesis in Section 1.2. This is to provide support to teachers mainly by enhancing their awareness of student's collaboration when working in small groups; thus teachers can make more effective and informed decisions that consequently may improve instruction, collaboration and overall student's performance (Figure 3-1).

#### Thesis statement

To design, implement and evaluate the conceptual and technological infrastructure **that capture student's individual and collaborative** activities as they build **shared knowledge** at an **interactive tabletop** and analyse these data through Interaction **Data Analytics** techniques to provide support to teachers by enhancing their **awareness** of students' collaboration (**Chapter 3**).

Figure 3-1 Thesis statement and main aim of the conceptual framework.

The proposed two-fold solution consists in designing, implementing and evaluating the *conceptual framework* and the *technological infrastructure* that can *capture* student's interactions at an interactive tabletop (or a number of them in the classroom), *analyse* these data through Data Analytics techniques and *present* distilled key indicators to the teacher (or students, researchers, designers and virtual agents that can indirectly inform teachers) to improve their awareness, decision taking and control of student's collaborative learning processes.

Table 3-1 List of positive and negative affordances of interactive tabletops for learning.

Affordances of Interactive Tabletops for Learning	
Positive	Disappearing computers, embodiment in the environment (Streitz and Nixon, 2005).
	Direct interaction (Benko et al., 2009; Müller-Tomfelde and Fjeld, 2012)
	Mutual collaborative awareness (Müller-Tomfelde and Fjeld, 2012)
	Combining the advantages of the physical and digital worlds (Müller-Tomfelde and Fjeld, 2012).
	Large display and interactive areas (for collaboration) (Benko et al., 2009)
	Horizontal orientation (for parallel work) (Benko et al., 2009)
	Equal opportunities of contribution (Müller-Tomfelde and Fjeld, 2012)
Negative	Potential to make aspects of collaboration visible (Bachour et al., 2010)
	Not ergonomic for certain activities (Benko et al., 2009).
	Reading large amounts of text (Morris et al., 2007).
	Typing large amounts of text (Benko et al., 2009; Hinrichs et al., 2007).
	The provision of a virtual keyboard for text entry (Benko et al., 2009).
	Day to day regular tasks (Wigdor et al., 2007).
	Showing digital elements where orientation is important.
	Input precision (for finger touch) (Benko et al., 2009).
	Lack of standard applications (Benko et al., 2009).

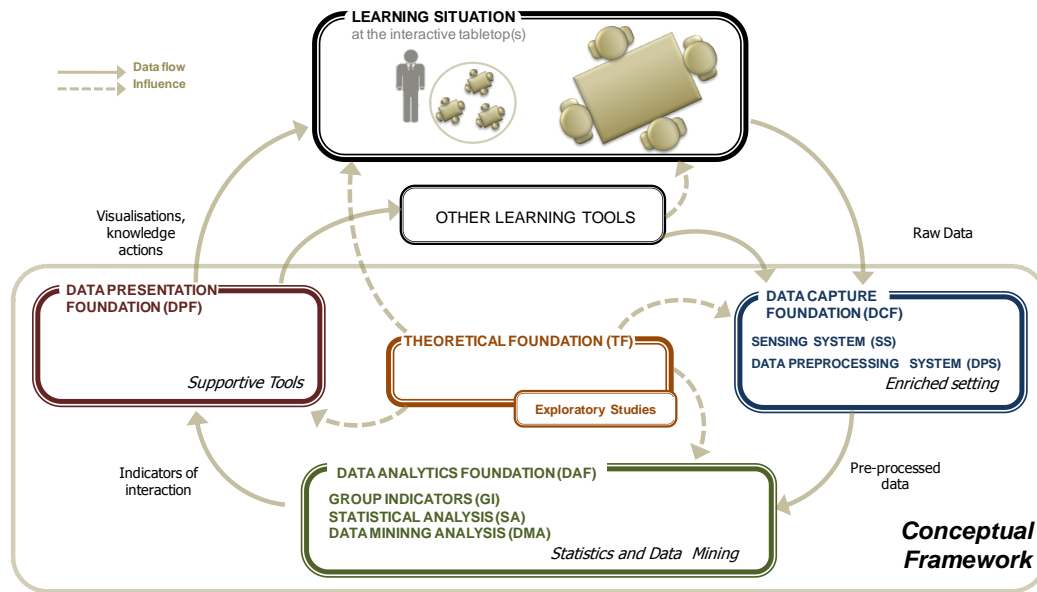
The next section describes our **conceptual framework designed to capture, integrate and analyse physical and verbal interactions in order to provide support to the collaborative learning activity at interactive tabletops**. The following sections describe each module of the framework. This chapter concludes with Section 3.8, which presents the mapping of each module of the conceptual framework to the associated thesis chapter where its implementation is described and evaluated.

## 3.2. The Conceptual Framework (TSCL-CF)

The Tabletop-Supported Collaborative Learning - Conceptual Framework (TSCL-CF) focuses on a specific learning situation in which the small group of students is the main unit of creation of collaborative knowledge. In this learning context, students mainly work face-to-face on a task that requires the creation of a joint solution; and students have egalitarian opportunities of participation and shared objectives. The type of learning environment provided by interactive tabletops represents an instance of the learning situation that TSCL-CF aims to support.

The main components in this conceptual framework are shown in Figure 3-2 (a more detailed diagram of the TSCL-CF can be found in the Appendix Section A.1). These include one central Theoretical Foundation (TF) that contains the main theories, principles or paradigms that drive the design, development and implementation of the learning activities and the educational technology; and three operational modules. These modules are: the *Data Capture Foundation* (DCF), the *Data Analytics Foundation* (DAF) and the *Data Presentation Foundation* (DPF). At mid-right of Figure 3-2, inside the blue box, we show the elements of the DCF: the *Data Sensing System*, SS, that captures the data from individual activity and group interactions from the face-to-face learning system; and *the Data Pre-processing System*, DPS, that is in charge of filtering, processing, integrating and adding sense, if needed, to the raw data captured by the SS in preparation for a deeper data analysis or to mirror distilled information to the target users.

The lower green box of Figure 3-2 shows the main elements of the DAF whose main objective is to analyse the pre-processed data from the DCF to either directly generate group indicators or to discover hidden patterns from interaction data. This component is strongly influenced by the theoretical foundation on Computer-Based Interaction Analysis adapted to face-to-face settings. The elements of the DAF are: a number of Group Indicators (GI) carefully selected to describe various aspects of student's interactions, a set of Statistical Analysis tools (SA) that include both descriptive and inferential statistical models, and Data Mining Analysis algorithms that can be used to discover patterns from student's data.



The learning situation that this framework aims to support is defined in terms of Collaborative Learning which is more likely to occur between people with a similar status. Building on Dillenbourg's work (1998), this learning situation is characterised by four aspects that are described as follows. The first criterion is that group members have *similar opportunities* to participate and the learning activity is meant to be open for all group members to contribute.

The third criterion is that in this situation students should share, or at least have, similar learning goals. This is in opposition to *competitive* contexts where there is a goal or reward that only one or a few students can achieve by outperforming the rest of the group members. The collaborative learning situations that we target are characterised by the presence of common goals, mutual rewards and shared resources to accomplish the joint task (Qin et al., 1995).

The fourth criterion distinguishes our target collaborative learning situation from *cooperation*. In *collaboration*, there can be a horizontal division of labour into, what it can be called, *reasoning layers* (Dillenbourg, 1998). For example, when one or more group members work on some low level task whilst other members work at a meta-level by providing arguments, information or instructions. By contrast, in *cooperative situations*, there can be a vertical division of work in which students might be involved in small different and independent sub-tasks (Oxford, 1997).

Additionally, we focus on two very well defined tabletop-based learning environments where the collaboration and instruction dynamics vary largely; these are settings where 1) *a single group* works at an interactive tabletop (the most common experimental scenario in tabletops research or for focused group work), and 2) *multiple tabletops deployed in a classroom*, an area of growing interest from the CSCL perspective (Mercier et al., 2012).

The learning situation also includes the *data sources* from which information can be captured by the technology: the group as a whole, individual contributions, the digital artefacts that students individually or collaboratively constructed before or after the group work, through the use of other *external learning tools*, and the artefacts that are used to mediate collaboration at the shared device. It additionally includes the *target users* the approach is aiming to aid, they typically are: (i) the learners, (ii) their teachers, (iii) researchers, or (iv) a learning tool or tutoring system itself.

Interactive tabletops may afford collaborative learning situations without enforcing interaction styles. We acknowledge that interactive tabletops can also be suitable for other kinds of learning situations (as discussed above, cooperative, competitive, asymmetric or uneven group work). However, we argue that our approach must be strongly backed up by well-established theories that can serve as scaffolding for designing all the conceptual and technological elements of the solution. As mentioned in Chapter 2, in this thesis the main theory that underpins the framework is *Group Cognition* which complies with the definition of a collaborative learning situation defined in this section. We present details of this Theoretical Foundation (TF) in the next section.

### 3.4. Theoretical Foundation (TF)

The Theoretical Foundation (TF) of the TSCL-Conceptual Framework has the purpose of driving the formulation of the approach for collecting and sensing student's interactions, validating the usage of analytics tools to explore the large amounts of student's data, providing sense and a higher level of abstraction to student's actions and scaffolding the implementations of the solution, from theory into practice. The theoretical foundation can offer principles for the implementation of the framework to specify, for example, the student's data that should be captured, the type of group indicators that can provide better insights of collaboration and the ways in which the approach can be useful for teachers or students to enhance the teaching-learning experience. A fully discussion of the elements was provided in Chapter 2 (Background, Section 2.2).

Table 3.2 presents the main principles that provide the foundation for the implementation of the TSCL-CF in this thesis. These are the theory of *Group Cognition* (Stahl, 2006) which builds on top of *collaborative knowledge building* (Scardamalia and Bereiter, 2006) and well established principles of *mediated cognition* (Vygotsky, 1978) and *distributed cognition* (Suchman, 1987; Winograd and Flores, 1985). The theory of Group Cognition provides a solid theoretical grounding for all the modules of the framework including the definition of the learning situation.

Another area that provides a foundation for our approach is the research work on Computer Based Interaction Analysis. This is a discipline which has focused on exploring and producing indicators of collaborative learning to provide support or enhance awareness to the participants of the group processes. These usually are the students and their teachers. Other agents involved, who may also be interested in the enhancement of these processes include researchers, designers and administrators. This research area seeks to develop solutions that can offer automated support at different levels, from visualisations of group indicators that can be unintrusively displayed, to more

invasive actions performed by the system to aid students if possible problems are detected (Soller et al., 2005). Similar approaches coming from Artificial Intelligence in Education (IAED) and Educational Data Mining (EDM) aim to exploit student's data to discover patterns in educational datasets, model students skills, their weaknesses, or find trends of interaction that lead to either succesful outcomes or underperforming behaviours (Baker and Yacef, 2009).

The third set of principles that provides a grounding for the implementation of the framework in authentic learning scenarios is the concept of *Orchestration* (Dillenbourg et al., 2011). This paradigm highlights the importance of offering simple but effective solutions to real problems in the classroom. It promotes what is called *modest computing*, that implies the application of minimalist approaches to mirror key aspects of the classroom or the students that would otherwise remain unseen, instead of elaborating complex student models. Prieto et al. (2011) pointed out that research and practice on orchestration has gone beyond the classroom. Orchestration does not only addresses teacher's in-class needs on improving planning, control and awareness during the activities in the classroom but also the consideration of models, theories, and practices for the teacher to integrate their available tools across different contexts (classroom, home, tutorials, field trips, small group collaboration, etc). Principles of Orchestration are very important for designing the means to show information to teachers and for implementing learning scenarios with multiple tabletops in the classroom.

Table 3-2 Main principles of the Theoretical Foundation (TF).

Theoretical principles	Description	Key references
<b>Group Cognition theory</b>	Group Cognition (Stahl, 2006) considers the small group activity as a process that is focused on constructing new understanding and in which shared meaning is created across the utterances of different learners. Both abstract and physical artefacts created by learners contain parts of the mutual understanding generated by the group and are used as mediators of the collaborative activity.	(Stahl, 2006) (Vygotsky, 1978) (Scardamalia and Bereiter, 2006)
<b>Computer-Based Interaction Analysis</b>	The aim of this approach is to provide information directly to the participants of the learning activities (usually students or teachers), to self-assess their activity or improve the performance of the learning process. This goal is partly shared by the fields of Artificial Intelligence and Data Mining in Education (Baker and Yacef, 2009).	(Dimitracopoulou et al., 2004) (Soller et al., 2005) (Soller and Lesgold, 2007)
<b>Classroom Orchestration</b>	Orchestration is the process of coordination of the available resources, multiple learning activities occurring at various social levels, and the stakeholders involved in and out the classroom (Prieto et al., 2011).	(Dillenbourg and Jermann, 2010) (Dillenbourg et al., 2011) (Prieto et al., 2011)

### 3.5. Data Capture Foundation (DCF)

The Data Capture Foundation (DCF) is the component that collects and gathers rich student data from the face-to-face learning environment. It also considers the various ways to record the low level raw interaction data along with contextual information that can provide meaning, in terms of learning and collaboration, to user interface action logs. A large number of studies in the CSCL field underline the importance of analysing the conversation between group members (Jeong and Hmelo-Silver, 2010). However, in face-to-face settings there are multiple channels that group members use to communicate, starting with verbal utterances but also enriching the communication with non-verbal cues. The analysis of utterances has proved crucial to understand what is actually going on within a group in terms of collaboration (Stahl, 2006). This type of analysis still mostly requires the manual scrutiny of video recordings making the results of such analysis very useful for research but less suitable for deploying a technological solution that can directly aid teachers or students.

Alternatively, previous studies exploring the capture and analysis of verbal participation at non-interactive tabletops have shown that even modest indicators of speech can be effective to describe

several aspects of face-to-face collaboration (Roman et al., 2012). These include interaction patterns, the evolution of the speech flow, leadership and behavioural changes. As discussed in Section 2.3.2., the automated analysis of verbal participation at interactive tabletops is an important aspect that has not been deeply explored. Additionally, according to the theory of Group Cognition, an additional way to know about the group knowledge is through the analysis of the artefacts created by the groups. Previous research has investigated the impact of multi-user interactions afforded by tabletops on certain aspects of collaboration such as equity of participation and self-regulation (Marshall et al., 2008). A deep understanding of the connection between the artefacts produced, verbal activity and physical interactions at the tabletop is still lacking.

Figure 3-3 shows the elements that are closely related to the DCF. The boxes located at the upper-left and lower-left of the figure illustrate how the nature of the learning environment (whether it is a single device placed under controlled conditions or an uncontrolled real classroom) and the theoretical foundation of the approach greatly influence the type of data that *should* and *can* be captured. The *internal* sources of data include the group activity, individual participation and student's artefacts. However, there can also be *external* sources of student's information in the form of other learning tools that can be inter-connected within the learning ecology. These can include desktop-based or online-based Personal Learning Environments (PLE's) that students can use to perform activities previous to or after the use of interactive tabletops. Other learning tools displayed on mobile devices can be used outside or within the classroom (Valdes et al., 2012). Moreover, centralised Learning Management Systems (LMS's) or Virtual Learning Environments (VLE's) that are often used by teachers to coordinate a complete course (e.g. Moodle, BlackBoard or Trac) can provide integral information about each group, individual students and products from other learning activities that may be relevant for the collaborative work at the tabletop (Figure 3-3, top-right).

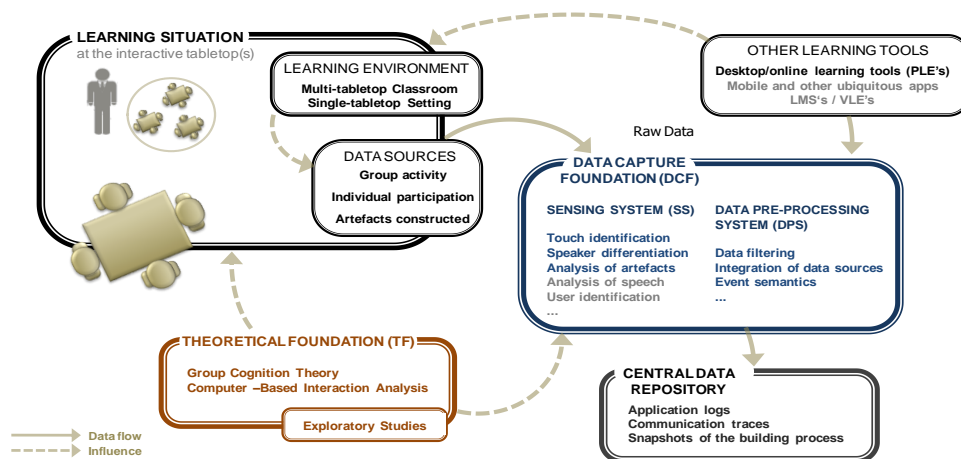


Figure 3-3 TSCl- Conceptual Framework sub-diagram focused on the Data Capture Foundation (DCF).

An initial key question that drives the implementation of the DCF is: *What data is needed to be captured in order to derive group indicators?* Dimitracopoulou et al. (2004) defined a taxonomy of group indicators that can automatically be captured and processed from non-face-to-face learning systems. This taxonomy sets an initial standard, which can be extended to face-to-face settings, to define what data should be captured by a collaborative learning system that aims to produce indicators of group activity. It distinguishes five sources of information for analysing the collaborative process: (i) individuals (the actions and products of specific learners), (ii) undifferentiated group (information that concerns the whole group, without identifying individual contributions or roles), (iii) differentiated group (information in which the contribution of each learner is identified), (iv) the community (considering multiple groups), and (v) the society or community). Our approach concerns the first four points of view. These are part of the Data Sources box in Figure 3-3.

The second crucial question is: *What data can be captured at a tabletop-based learning environment?* In face-to-face environments there is substantially more information being externalised by learners in comparison with networked applications (Olson et al., 2002). The



collaborative situation and channels of communication are significantly different in collocated settings. Therefore, the extent to which the technology can capture student's interactions may impose significant limitations on what can actually be captured at a face-to-face setting (Yu and Nakamura, 2010). As stated earlier, most research on tabletops in education relies on video analysis and techniques that require human judgement. Most tabletop hardware cannot unobtrusively distinguish who touches the surface or speaks; or the timing, order, actions in parallel and meaning of the physical actions is not considered.

The output of the component consists of rich data that contains contextual student's information integrated by the synchronisation of a number of data sources that can be further analysed or shown directly to the target users. From a more technical perspective, these output data are recorded into a shared *Central Data Repository* to allow other services to access the information in-time (see Figure 3-3, bottom-right). The DCF aims to accomplish two main operations: *sensing* and *pre-processing*. More details regarding these two components are provided in the next sub-sections.

### 3.5.1. Data Sensing System (SS)

The *Data Sensing System* (SS) consists of the hardware and software that can be used to capture any type of student's actions (or inactivity) from the physical collocated environment or by accessing student's data from other sources such as student models, online learning systems or teacher's notes. Section 2.3.2 described in detail the affordances of interactive tabletops to capture user's interactions when they are enhanced with other sensing devices.

Table 3-3 presents an overview of the main categories of sensing technologies that can be used to enrich interactive tabletops. The basic contextual data that is mostly not captured by interactive tabletop hardware is the information of identified touch. Section 2.3.2 presented a number of methods to provide tabletops affordances to identify who is doing what, showing that most of the solutions are intrusive (Marquardt et al., 2010; Meyer and Schmidt, 2010), require training (Zhang et al., 2012) or are highly coupled to the touch sensitive technology, like the cases of the DiamondTouch (Dietz and Leigh, 2001) or the use of pens. These limitations in previous work make it difficult to deploy realistic solutions for classroom implementations. Speaker differentiation has been explored in non-interactive tabletop collaborative systems (Evans et al., 2010; McCowan et al., 2005; Roman et al., 2012) and proved to be effective in providing quantitative information that can be associated with a deeper analysis of the content of the conversation. Another source of student information come from analysing the artefacts produced on the tabletops to provide insights into group collaboration. This approach has mostly been inspired on research on CSCL adapted to tabletop applications (Kharrufa et al., 2009).

There are other sensing technologies that can be applied to tabletop environments to enrich the collection of interaction data. The automatic analysis of speech is a sensing technology that has improved in recent years and that offers great promise to help teachers to enhance their awareness of student's interactions (Rosé et al., 2008). Eye tracking technologies have been explored at tabletops to improve the interaction with distant objects and for providing other awareness to the software applications (Holman, 2007; Mauderer et al., 2013). However, these explorations have not tackled the implementation of multi-user solutions that can be used in non-controlled conditions, partly because of limitations in the current technological infrastructure. More modest sensing is possible including, for example, the detection of attention by identifying head direction using automatic video analysis (McCowan et al., 2005) or advanced extraction of audio features such as pitch level, energy or speaking speed and tone of voice (Kim et al., 2008).

The development of sensing technology is not the real driver for effective data capture. There is a need for exploratory studies to justify the use of any added sensor in a collaborative learning environment. Chapter 4 of this thesis presents studies on other datasets that address questions about what data can be captured and the analyses that can be performed with it. Choosing appropriate sensing technology has a direct impact on the cost-benefit relationship of the proposed solution and on the feasibility for its deployment in authentic settings.

Table 3-3 Overview of sensing technology enriching interactive tabletops.

Sensing information	Description	Key previous explorations
<b>Touch identification</b>	Associating individual touches with different users without necessarily identifying the person.	(Dietz and Leigh, 2001) (Zhang et al., 2012) (Marquardt et al., 2010; Meyer and Schmidt, 2010)
<b>Speaker differentiation</b>	Speaker differentiation has been used in collocated environments to automatically mirror levels of participation. No previous exploration in <i>interactive</i> tabletops.	(Bachour et al., 2010) (Roman et al., 2012)
<b>Analysis of artefacts</b>	The analysis of the progress of the solution created by a group at the tabletop that can reflect key information of group member's understanding.	(Kharrufa et al., 2009)
<b>User identification</b>	Association of touch activity with an authenticated user at the tabletop. Not yet much explored in tabletop environments.	(Ackad et al., 2012)
<b>Automated analysis of speech</b>	No previous exploration in tabletop environments.	-
<b>Gaze tracking</b>	Gaze tracking has been explored in tabletop settings to enhance user's reach and text orientation.	(Holman, 2007) (Mauderer et al., 2013)
<b>Connection with other user applications</b>	Some previous exploration of access of tabletops to data previously produced by learners in other environments and devices (e.g. web and mobile interfaces).	(Valdes et al., 2012)

### 3.5.2. Data Pre-processing System (DPS)

The second element of the DCF is the *Data Pre-processing System* (DPS). This system is strongly influenced by the Theoretical Foundation which informs what information and, more specifically, which indicators can provide insights into the nature of collaboration and learning within groups. The three main objectives of this component are: data filtering, the aggregation of data coming from multiple sources and the addition of meaning of events beyond the low level logged application actions. Sensors may be permanently active collecting data. However, only some of these data may be relevant for the teachers, researchers or students themselves. Data filtering steps are frequently needed to select the information that is relevant for the analysis tools, or to be displayed to the users. This filtering makes it easier to analyse or show student's data, by hiding the data that the target users temporarily want to take out of view.

Secondly, multiple sensors can record events in parallel using different formats. A key principle for deploying a solution according to our proposed framework is the synchronisation and integration of data coming from multiple sources and at different levels. For example, in a single tabletop, the actions of a student within a group might be recorded in the form of differentiated audio logs and touch interactions. These data should be integrated to be able to associate patterns of both verbal and touch participation. Moreover, in settings with multiple small groups working in parallel, all the software being used by each group should synchronise their logging systems with a common service, so that the whole system can highlight events that occur at a class level and not only within small groups. Additionally, all the tools and actions performed by the teacher through any controlling or monitoring tool, should be synchronised to give the analysis tools more flexibility to *triangulate evidence* to discover key aspects of collaboration and learning. The provision of a centralised data repository is a suitable implementation that offers synchronisation and high availability of the data source. The synchronisation also allows the system to associate these multiple sources of information with what we call, *event semantics*. These are higher level meanings associated with student's actions that contain added contextual information in contrast with low level actions, such as touch or click events, that may not be informative enough in educational situations.

### 3.6. Data Analytics Foundation (DAF)

The Data Analytics Foundation (DAF) is the component that processes the filtered student's data integrated from multiple sources by the DCF. The DAF can scrutinise the captured data to produce key indicators of interaction or patterns linked with strategies followed by students.

Figure 3-4 shows the elements of the DAF and the components of the framework that the DAF is directly related with. These components include the Central Data Repository that the DAF services can have access in order to process the data either in *real-time*, while the learning activity is occurring, or for post-hoc analysis. The DAF itself can introduce new information to the Repository including indicators of group interaction, and partial or final results of the data analyses. The Theoretical Foundation (TF) also influences this component, especially for the definition of Group Indicators (GI). And finally, other external *Models of Group Work*, created in particular learning situations, can be used by the DAF to derive indicators that may fit such models. Learner models gathered by external platforms can also provide input for the data processing of the DAF.

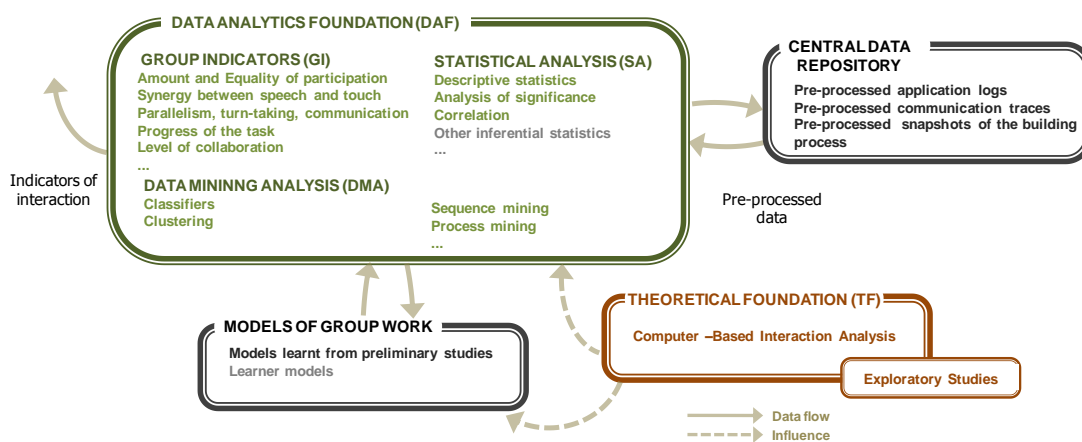


Figure 3-4 TSCL-Conceptual Framework sub-diagram focused on the Data Analysis Foundation (DAF).

The first element of the DAF is a set of Group Indicators (GI) that provides information about different aspects of student's work and relationships. These GI's should be grounded on elements of the TF. In this thesis the set of GI are mainly borrowed from the extensive research in the field of Computer-Supported Interaction Analysis. Some of these indicators include quantitative measures of participation, contribution, symmetry among student's actions, interweaving of the stream of conversational activity and actions on the shared device and the degree of collaboration of the group. Other derived aspects are considered such as parallelism, turn taking, patterns of communication and leadership. Indicators of group performance are also obtained from the analysis of artefacts under construction that can provide information about the progress and quality of the group task.

The two operational elements of the DAF that perform this generation of indicators are the Statistical Analysis (SA) and the Data Mining Analysis (DMA) systems. The SA refers to descriptive statistical approaches that can be used to group measures, extract averages and make simple comparisons of student's data that can be easily visualised. Inferential statistics can also be applied to provide deeper data analysis such as finding correlations or trends in large amounts of data.

The DMA includes the application of tools that can address questions that concern possible trends in activity, or when it is desirable to find models that better describe learning aspects of group collaboration. Some of the techniques applied in this thesis include classifying algorithms, clustering approaches, sequence pattern mining and process mining models. Regardless of the methods used to generate group indicators, these generally are concerned with aspects of collaboration, argumentation, participation, awareness and content (Dimitracopoulou et al., 2004). Table 3-4 presents an overview of some of these categories of group indicators.

Table 3-4 Main groups of Indicators of Group Interaction (Dimitracopoulou et al., 2004). Group indicators that have been explored and used in this thesis are highlighted in bold.

Indicator level	Description	Example indicators
High level indicators related to collaboration	Offer some autonomous interpretative value of quality, modes, state or structures of collaboration.	<b>Conversation and action balance, division of labour, actor's degree centrality, network density, collaboration level in the group.</b>
Elaborated indicators of collaboration quality	Describe measures of aspects of discussion that happened within the groups. Their automatic generation mostly applies to systems that scaffold argumentation.	Amount of collaborative work, argumentation, coordination, cooperation, collaboration.
Elaborated indicators of argumentation quality	Quantify qualitative aspects of argumentation. Automatic generation mostly apply to systems that scaffold argumentation.	Initiative, elaboration, creativity, conformity, <b>opinion difference visualisation.</b>
Low level indicators of argumentation quality	Reflect quantitative measures of argumentation activity that can be captured through a number of learning systems.	<b>Average number of contributions, average contribution size, group interactivity, contributions answered by others, follow-up contributions.</b>
Indicators of participation	Include general indicators of individual amount and proportion of student's participation	<b>Learner's ratio of participation, participation percentage, participation count, non-verbal actions, number of messages per participant, student contribution, interactions, active students.</b>
Content related indicators	Provide information from the content or artefacts generated by students as a result of their collaborative activity.	<b>Classification of actions, inserted (or deleted) "Items" per participant, monitoring experiment outcomes.</b>
Cognitive indicators related to strategies	Indicators with high levels of abstraction that are processed manually (but that can still aid group's analysis).	<b>Heuristics use</b> , discovery learning, knowledge development, in discovery learning processes.

*Low level actions* are those performed by students and that can be captured by the system with no much contextual information about their learning impact. *High level actions* provide more information about the quality of collaboration or participation in terms of learning concepts. The higher the level of indicators is, the more interpretative value they have. Low level indicators provide information that requires more interpretation from the users' perspective, an aspect that may be desirable in some situations where, for example, a teacher uses indicators just to be aware of students who may be facing some learning difficulties. *Elaborated indicators* can also be obtained that provide a high level of interpreted information about student collaboration or performance for aspects that require either manual processing or a learning system that scaffolds most of the student's argumentation process (Schwartz, 1998). Table 3-4 presents examples of some group indicators that can be produced automatically in some types of learning environments. The discussion of the implementation of some of these group indicators in collaborative tabletop systems and similar collocated settings are discussed in the following chapters.

### 3.7. Data Presentation Foundation (DPF)

The Data Presentation Foundation (DPF) is the component of the framework that consists of the user interface elements that can provide the target users with key information about group work. As shown in Figure 3-5, the DPF is composed support tools that provide a range of services to the target users at different levels of information, intrusiveness and with varied objectives. The DPF has the potential to provide the target users with results of the data analysis, for example, in the form of a teacher's dashboard or knowledge, with the purpose of enhancing awareness or facilitating assessment and evaluation. The input of the DPF mostly consists of indicators that are obtained from the pre-processed captured student's data or aggregation of these using descriptive statistics. Key findings obtained from using artificial intelligence approaches or inferential statistics can also be shown directly to teachers or students. They can further be used to drive adaptive responses from the system or to inform researchers and designers about the nature of the collaborative processes.

The appropriate type of output information to be provided by the DPF firstly depends on the context of usage. Figure 3-5 proposes two main contexts. When the learning situation is a classroom,

teachers and students may need *real-time* information that can be delivered with the objective to afford changes in the collaborative processes at the time where actions can be taken to improve learning. Teachers and students are the main target users for *real-time* usage. However, the classroom data can also be used for after-class reflection. In this case, the target users can include the teachers who want to know the details of various aspects of the sessions; also for students to reflect on their own performance, and also for designers and researchers aiming to improve the learning tools or instruction approaches.

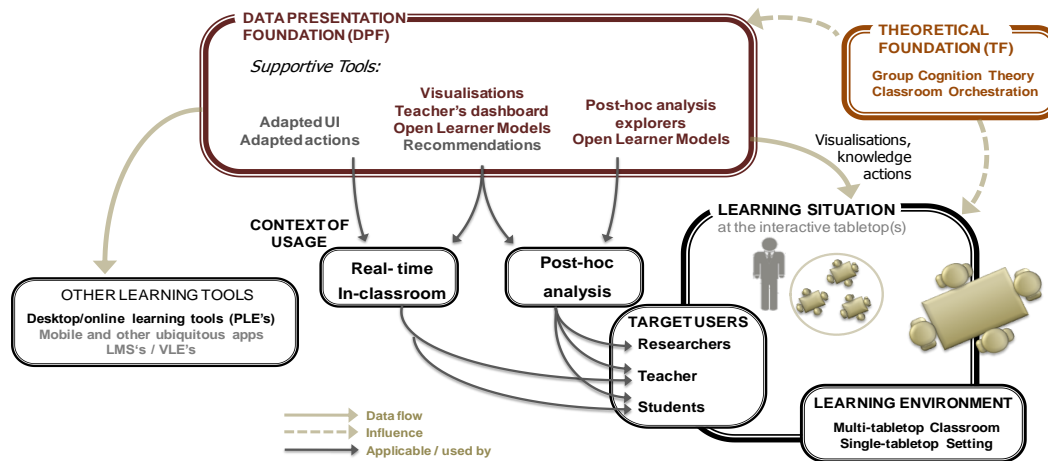


Figure 3-5 TSCL-Conceptual Framework sub-diagram focused on the Data Presentation Foundation (DPF).

The type of information provided to the target users can be identified by the times at which it is accessed and the degree of detail of the group indicators. Very detailed information about groups can be overwhelming and therefore their application in authentic scenarios will not be successful. Tools to visualise student's progress might be desirable for post-hoc analysis if the teacher is interested in some groups that might be problematic and wants to find evidence of possible causes of problems. However, large amounts of information in classroom time are not useful, since teachers need to invest most of their time into attending groups. Teachers need different levels of information for in-class use and for after class exploration (Bull et al., 2012). Moreover, key group indicators can be fed into other external learning tools, such as Learning Management Systems (LMS's and VLE's), to provide continued awareness about student's performance.

The Theoretical Foundation has informed the application of the DPF. The theory of Group Cognition, and studies that have explored the information that teachers require to enhance their teaching, can drive the design of the support tools. When implemented in the classroom, the principles of orchestration are relevant as they highlight the roles of the teacher and the technology to provide enhanced planning, design, awareness and control over all the classroom activities. The possible implementations of the TSCL-CF can provide key information to be used by three classes of stakeholders: by teachers in and after class; by researchers to explore different aspects of collaborative learning; or by designers to implement tutoring systems in the future. Real-time visual information of the group process can be designed to be shown to the teacher in private, or directly to the students. This thesis focuses on providing suitable forms of student's data for teachers and researcher. Therefore in most of the studies described in further chapters students are not provided with group indicators. While this information has the potential to be valuable for students, this is beyond of the scope of this thesis.

### 3.8. Implications for the Implementation of the TSCL-CF

There are a number of implications to consider for implementing interactive tabletop solutions to support collaborative learning grounded on the TSCL-Conceptual Framework. The first challenge is posed by the current limitations of tabletop devices. These offer limited ways to capture user's actions, with the exception of a few systems (Annett et al., 2011; Ballendat et al., 2010; Dietz and

Leigh, 2001). Even basic features, such as user differentiation at the tabletop, are not provided by the current majority of current hardware tabletop products. Beyond the hardware limitations for data capturing, there is also little research on guidelines to provide effective ways to foster collaborative learning in authentic scenarios. Scott et al. (2003) presented a series of design guidelines for tabletop-based systems that support collaborative work but considering only one tabletop. In a real learning scenarios, tabletops will be valuable if deployed to support activities where multiple small groups are collaborating in parallel (AlAgha et al., 2010). For this context, existing guidelines are informative but not adequate. Moreover, design guidelines for mining collocated data just do not exist. Another key aspect for the implementation of the framework is the design of learning tasks. These should have the versatility to be useful in both the classroom and laboratory spaces, or even in other contexts such as informal learning spaces.

Figure 3-6 presents the mapping between the elements of the TSCL-CF and the description of the implementation of each in the chapters of the thesis. The TF has been described in Chapter 2 and will be completed through a number of exploratory studies on collaborative learning in collocated settings that were conducted and are described in Chapter 4. The DCF is primarily presented in Chapter 5, including the development of both the learning environment and the sensing systems. The DAF is presented along with each of the studies of the thesis. However, the implementation of this component is mainly presented in our larger studies in the lab and in the classroom, described in Chapter 7 and 8. Chapter 6 presents the implementation and evaluation of the DPF. As shown in Figure 3-6, Chapter 8 presents the integration of the framework, applied in a multi-tabletop classroom; this is the final outcome of the research work of this thesis.

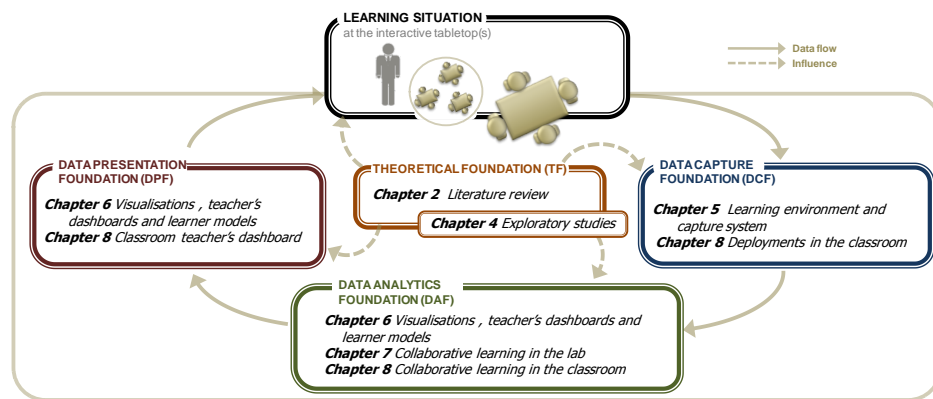


Figure 3-6 Simplified conceptual framework mapping the chapters of the thesis.

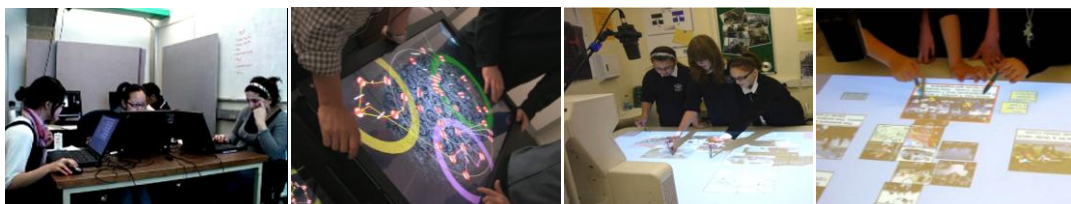
### 3.9. Chapter Summary

This chapter described the Tabletop-Supported Collaborative Learning-Conceptual Framework (TSCL-CF) which provides the scaffolding to the approach and contributions of this thesis. The TSCL-CF focuses on the flow of student's data that can be captured, filtered, processes, analysed and shown back to the users of the learning environment to enhance the collaborative processes. The framework is strongly grounded on principles on CSCL, but also on exploratory studies performed in other areas such as EDM and HCI. The rest of the framework consist of three operational components or foundations, each focused on the data capture, analysis and presentation of key indicators to teachers, students, designers, researchers or to be used by other technological agents. We propose that this framework can be used as a basis to build support mechanisms for tabletop-based collaborative learning systems. This thesis presents the implementation of a number of instances of the framework in a set of different learning contexts. These studies serve to provide validation of the framework and show its applicability in the real-world.

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## Chapter 4: Exploring Other Datasets for Analysing Face-to-face Collaboration

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*"The greatest obstacle to discovering the shape of the earth, the continents and the ocean was not ignorance but the illusion of knowledge"*  
-Daniel J. Boorstin

**Summary:** This chapter presents three studies based on the analysis of data from collaborative learning settings previously collected by other fellow researchers. These include a multi-display setting used to resolve optimisation problems, a prototype of our multi-touch concept mapping application and a pen-based system for problem resolution. The purpose of this chapter is to explore how data analytics techniques can be used to discover patterns of interaction from student's data. We aim to explain whether student's data can be automatically analysed to reveal key aspects of group's interaction around educational groupware. The techniques used in these studies include *user modelling* and *data mining* algorithms such as classifiers, clustering and sequence pattern mining. The chapter concludes with a discussion of the main considerations and requirements for designing a data-driven approach to support face-to-face collaboration aided by groupware devices.<sup>1</sup>

### 4.1. Introduction

As was stated in Chapter 1, and discussed in detail in Chapter 2, there is little research on developing tools that can automatically analyse student's face-to-face collaboration. This is critical in order to design systems that can automatically adapt to the state of the collaboration processes or that enhance teacher's awareness of small group work at the classroom. Our literature review showed that even though there is a growing interest in the use of interactive tabletops in education, there are not many explorations on the use of data mining or analysis techniques for face-to-face collaboration (Sections 2.4.2 and 2.2.2). However, the substantial research work on analysing *student collaboration* mediated by networked systems (Soller et al., 2005) can serve as a foundation to explore techniques also suitable for collocated environments. **The goal of this chapter is to gain understanding on ways to apply data analytics techniques on student's data that can be captured from face-to-face environments** (see Figure 4-1). To achieve this, this chapter presents three studies analysing data previously collected in three face-to-face learning environments: i) a multi-display

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<sup>1</sup> Parts of this chapter have been published in international conference proceedings of AIED 2011 (Martinez-Maldonado et al., 2011e), UMAP 2011 (Martinez-Maldonado et al., 2011c) and EDM 2011 (Martinez-Maldonado et al., 2011f).



environment in which students were asked to solve an optimisation problem, ii) an initial version of our concept mapping multi-touch tabletop application, and iii) a pen-based tabletop tool, called ‘Digital Mysteries’, that allowed school children to gather information from virtual content presented by the application in order to collaboratively produce an answer to a decision-making situation. The first and the third studies (i and iii) were conducted by other fellow researchers without the specific intention of performing further data analysis.

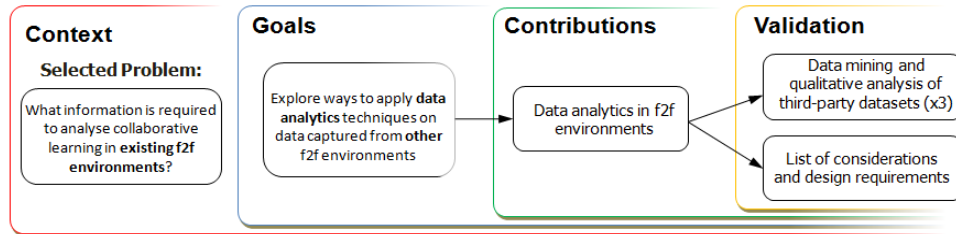


Figure 4-1 Context, goals, contributions and validation of Chapter 4.

The three studies presented in this chapter explore ways to apply data analytics techniques that are validated by triangulating evidence obtained from qualitative observations. The techniques applied in these cases are linked and can be used to provide three different forms of information:

1. **Study 1: Classifying “periods of collaboration” (at a multi-display setting);** this presents the design and evaluation of an approach that *classifies* periods of group work according to their level of collaboration. We tested a number of algorithms that analyse a number of features such as amount and symmetry of verbal and physical participation, to provide a general indicator of how collaborative a group performed.
2. **Study 2: Modelling symmetry as an indicator of group collaboration (at a multi-display setting and the tabletop);** this presents a group (user) modelling approach that explores the use of simple rules to provide insights on learners collaboration. It builds on the previous study to classify periods of collaboration by simplifying the classification models into a rule-based model and clustering. It also validates the applicability of this approach in both the multi-display and tabletop settings.
3. **Study 3: Mining patterns that distinguish high from low collaboration (at the tabletop);** this presents a data mining approach to discover patterns that can be associated with strategies that differentiate high from low achieving groups. This study complements the other two studies by proposing a mechanism to discover hidden patterns from students’ logged interactions. Sequence pattern mining and clustering algorithms are applied in this study.

The next section presents the study that explores ways to classify “periods of collaboration”. This study is grounded on the data analysis collected by the first multi-display environment (i). Section 4.3 describes the group modelling approach. This study makes use of data collected from the multi-display system (i) and our initial multi-touch concept mapping environment (ii). Section 4.4 describes the sequential pattern mining approach. This study is conducted on student’s data collected from the pen-based tabletop tool (iii) that provides an environment that is closer to the type of learning setting targeted in this thesis. The expected outcome of the exploratory studies presented in this chapter is **a set of insights into the feasibility of and the design requirements for automatically analysed collaboration in face-to-face settings.**

## 4.2. Classifying Periods of Collaboration

Detecting the presence or absence of collaboration during group work is important for providing help and feedback during learning sessions<sup>1</sup>. This first study explores an approach which automatically distinguishes between the times when a collocated group of learners, using a problem

<sup>1</sup> Parts of this section have been published in the proceedings of AIED 2011 (Martinez-Maldonado et al., 2011e).



solving computer-based environment, is engaged in collaborative, non-collaborative or somewhat collaborative behaviour. We exploit the available information from this dataset, audio and application log traces, to automatically infer useful aspects of group collaboration and propose a set of features to code them. We then use a set of classifiers and evaluate whether their results accurately match the observations made on video-recordings. Results show up to 69.4% accuracy (depending on the classifier) and an error rate for extreme misclassification (e.g. when a collaborative episode is classified as non-collaborative, or vice-versa) less than 7.6%. We conclude that this technique can be useful to show the teacher and learners an indication of the extent of their collaboration so they can become aware of it. The capture of the dataset using for this study was carried out by researchers of the University of Waterloo, Canada. For this reason, this study will be referenced in the rest of the thesis as *Study Waterloo 1*.

### 4.2.1. Motivation

In Chapter 1, we described the significant learning benefits of collaboration when students work in small groups (Stahl, 2009). We also proposed that emerging uses of technology offer the possibility of automatically capturing data that then can be used to detect and model the level of collaboration of a group. We have also discussed that there are several ways in which such models might be used, including mirroring information of the group to the learners and their teachers or improving the provision of support in CSCL systems (Soller et al., 2005). In the latter case, these environments are sometimes designed to encourage learners to collaborate or it can present structured tasks that force collaboration and participation. However, a general issue in applying these strategies is that different types of supportive actions can have different effects on the learning processes (Hattie and Timperley, 2007). Specifically in collaborative learning environments, it has been shown that help is more effective if delivered just when it is needed (Chaudhuri et al., 2009). Otherwise, well functioning groups may be distracted by unnecessary interventions. Meanwhile, groups that experience problems and do not collaborate may benefit from such interventions.

The goal of this study is to explore ways to exploit readily available data to determine what we can call “level of collaboration”. This can be described in terms of what the system can recognise as a collaborative situation by learning from qualitative observations performed by humans. This “level of collaboration” can provide a modest indicator for a teacher to identify groups that may need attention. We make use of two forms of data. One is the presence of speech, based on an audio feed from each learner, without analysing what is said (in this study this is collected manually). We call this a *simple audio trace*. The second source of data comes from the application log traces. From these two sources, we automatically infer key aspects of collaboration and propose a set of features to encode them to then be evaluated with a range of classifiers.

### 4.2.2. Context of the Study and Data Exploration

A given situation can be considered as “collaborative” in a learning context, if there are particular forms of interaction among the group members. For example, learning mechanisms such as explanation, negotiation, disagreement or elicitation (Stahl, 2009). We hypothesise that *it is possible to automatically infer whether a group of learners is engaged in a collaborative situation, from the application logs and audio traces, with a reasonable level of accuracy*. We first present the environment in which our data was collected.

#### *Participants and data collection.*

The original study this approach builds upon explored the impact of a multi-display environment on group processes (Wallace et al., 2009). For this study, data from 29 groups were used. Each group was formed by 3 students. Students worked together in the same room and on the same task, using multiple devices. These devices were: a personal computer per student, through which they could interact with a multi-user application in private; and a shared device, in the form of a public wall display showing the joint solution. Group members were seated around a table, each either facing or adjacent to the public display (see Figure 4-2, left). The seating positions were kept

constant for all groups. The interface visible on the laptops provided a personally tailored view of the workspace, where the resources that the owner could interact with were presented as more salient than the others. The shared display provided an overview of the progress of the group task (see Figure 4-2, right; not shown in Figure 4-2, left).

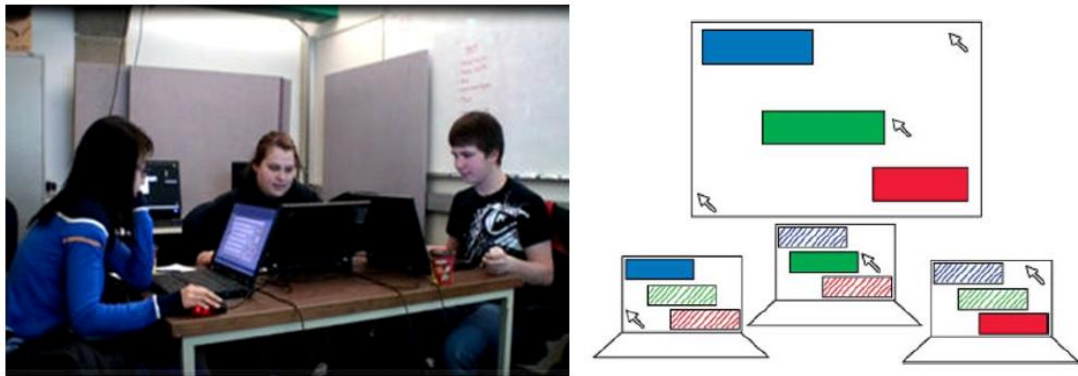


Figure 4-2 Multi-display setting. Left: Group of students solving a problem. Right: Configuration, group activity is shown in the public display, and an individual view of the task on personal displays (Wallace et al., 2009).

The 39 participants were students predominantly enrolled in university Maths, Science or Engineering courses and aged 18-27 years. Groups of 3 participants each were asked to perform a Job Shop Scheduling (JSS) task (Tan et al., 2008), which is an optimisation problem specifically designed for evaluating interactions within groups of learners. Participants were asked to optimise the scheduling of six *jobs*, each composed of six ordered operations. These operations require the use of six resources that can only be in use by one operation at a time. Participants can modify the interface, and therefore the solution, by dragging *resource pieces* into position with the shared goal of scheduling the completion of all six jobs in a minimal amount of time (Figure 4-3).

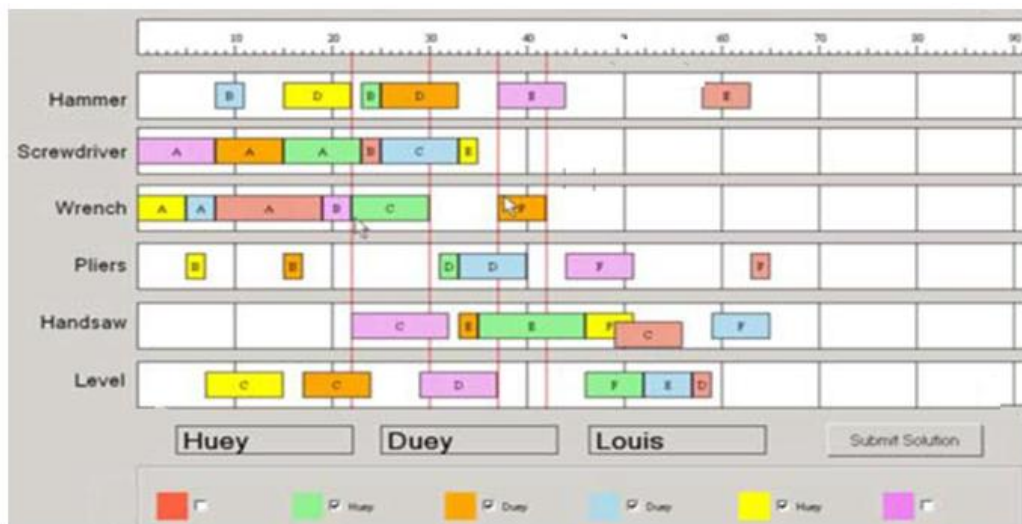


Figure 4-3 Job Shop Scheduling application screenshot (Wallace et al., 2009).

Each group was required to develop solutions for the JSS task 2 or 3 times. Groups spent 17 minutes per trial on average and executed between 100 and 600 *physical actions* per solution, for a total of 9,800 recorded mouse click or drag operations within the JSS software. In addition to the application logs, we also considered the transcribed verbal utterances for each session video-recorded session. Each complete unit of speech in spoken language produced by a learner was considered as a verbal participation. In general, most of group's speech was on-task. These transcripts included a total of 4,836 *verbal participations* which, combined with the physical action data, formed a dataset of more than 14,636 physical and verbal interactions (Table 4-1 illustrates example logs of the dataset).

Table 4-1 Samples from the JSS combined dataset.

Verbal Participation Log				Physical Action Log			
User	Start	End	Log	User	Start	End	Log
C	15:18	15:19	I'll take care of the a's	A	01:57	01:59	- Move resource A-
C	15:21	15:22	you do the c and the d's	C	01:58	01:59	- Move resource D -
A	15:22	15:23	Yea	B	02:02	02:04	- Move resource B-

#### Data exploration.

Before any data mining technique was performed, the data was examined to see whether any simple statistics could distinguish interesting differences between groups. Firstly, we calculated the total number of utterances, clicks and talking time for each group. Figure 4-4 shows the participation sequence diagrams of three sample groups. The top of each diagram shows the verbal participation and the lower parts represent the physical actions. The horizontal lines and rectangles represent actions or sets of actions (rectangles) performed by each author. The directed arrows indicate the relative sequence of the actions. From these diagrams, we observe that Group “K” was generally collaborative but participants A and C were more active. Group “L” did not have much verbal interaction, and from the diagram of physical actions, we observe they did not do much neither. Group “M” presents asymmetrical group activity: Student C has just three verbal actions, far less than the others in the group, but he performed most of the physical actions. These diagrams illustrate significant differences that exist between groups. These observations were confirmed by analysing the video recordings of the sessions.

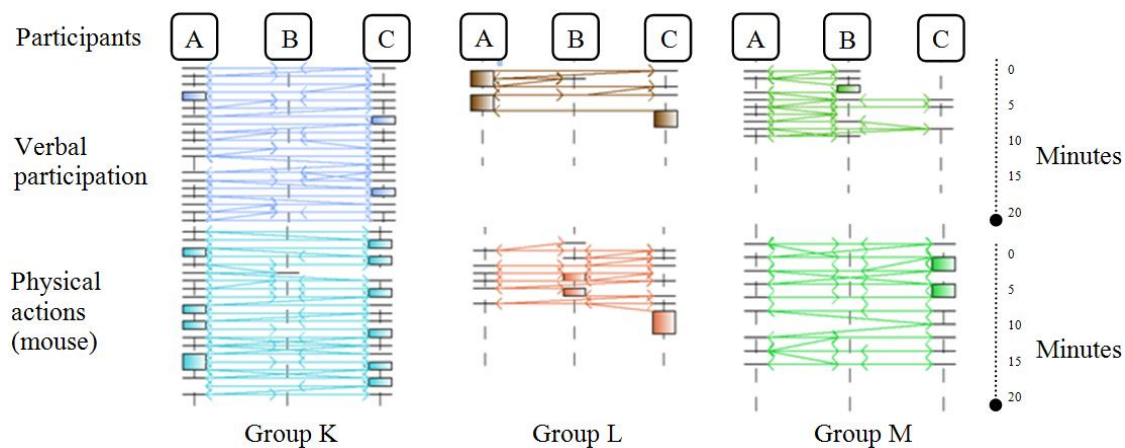


Figure 4-4 Representation of the verbal and physical participation of three groups. A participative group (left), a non-communicative group (centre) and an asymmetric group (right). Diagrams created using the Process Mining Framework (van Dongen et al., 2005).

### 4.2.3. Categorising Collaborative Learning Behaviour

Next, we describe the rest of the approach, which consists of collecting the logs of activity, constructing a set of features to learn these labels and applying different classifiers.

#### Data annotation.

Dillenbourg (1998) describes a situation as collaborative when participants are at the same level, can perform the same actions, have a common goal and work together. Building on these criteria, qualitative observations were made to assess whether each group was collaborating. Videos of each group’s sessions were observed. Each group’s activity was coded every 30 seconds based on the perception of collaboration for that block of time (as if a teacher was observing the group). Each block of activity was coded as matching one of three possible values, the highest being a *collaborative moment* (C), based on Dillenbourg’s definition of collaboration (Dillenbourg, 1998) described above. If all participants participated to some extent or they were aware of their peer’s

actions, then, that 30 seconds block of activity was tagged as *collaborative*. A time period was tagged as *somewhat collaborative* (SC) if one or two members were unaware of their peer's actions, or if the group failed to communicate but they still tried to collaborate at some level. The last possible value, *non-collaborative period* (NC), was assigned if the group split the task, worked separately, or if just one participant did all the work. A label was assigned to every 30 seconds block of activity for each group. Most of the observations were carried out by a single observer. Two different raters, including a domain expert, tagged a sample of 15% of the sessions. Inter-rater reliability was reasonably acceptable – Cohen's  $k = 0.69$ . All groups had the same time to solve the problem (20 minutes) but they were free to decide when to stop. Figure 4-5 (left) depicts examples of the coding of some sessions. A row with many blue blocks (C), some in orange (SC) and the few in light yellow (NC) correspond to very collaborative sessions.

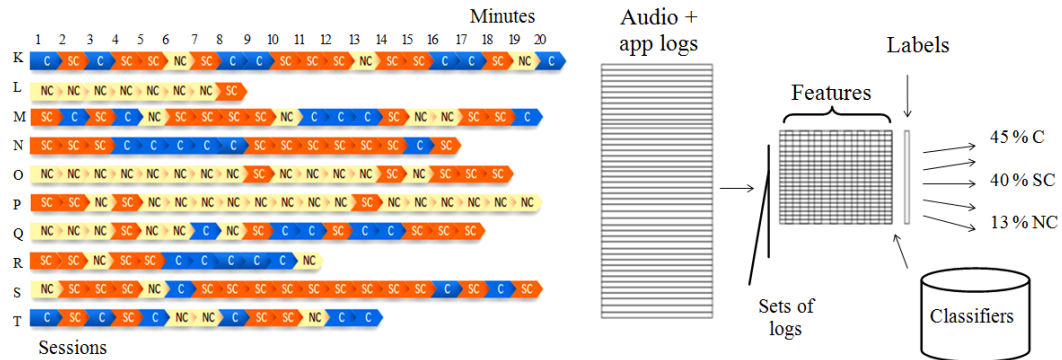


Figure 4-5 Annotation of blocks of activity. Left: Dot plot representations of the coding of some analysed sessions for each 30 seconds of group work tagged as *collaborative* (blue), *somewhat collaborative* (orange) or *non-collaborative* (yellow). Right: The architecture of the approach.

Then, the audio and application log lines were grouped forming sets of log lines (Figure 4-5, right). The grouping was done using three different block sizes: 30, 60 and 90 seconds. We chose these time frame sizes based on the observations made on the videos of the sessions. In a period of 30 seconds, we can observe complete dialogues related to a solution issue so we chose it as our minimal granularity. However, the conversations can last more than 30 seconds, so we also investigated the use of longer time-frames (60 and 90 seconds). For these, the label was obtained by implementing 60 and 90 second sliding windows with steps of 30 seconds and joining the underlying labelled blocks using the following rules when the labels were not uniform across the blocks: For 60 seconds:  $C+SC=C$ ,  $SC+NC=NC$ ,  $C+NC=SC$ . For 90 seconds:  $SC+SC+C=C$ ,  $C+SC+NC=SC$ ,  $NC+NC+*=NC$ ,  $C+C+*=C$ , etc. Using this process, we obtained three datasets of similar size (700 samples in average).

#### Feature selection.

Weinberger and Fischer (2006) defined two dimensions of the collaborative learning work that can be measured quantitatively. These are the amount and the heterogeneity of participation. Drawing on this, a number of features were calculated for each block. We propose a feature model that includes: quantity of physical and verbal participation (features 1, 2 and 3 in Table 4-2), number of active participants (feature 4) and the degree of dispersion of the participation among them (features 5, 6 and 7).

Table 4-2 Diagnosis features and six examples of 30 seconds blocks of collaborative (C1, C2), somewhat collaborative (SC1, SC2) and non-collaborative (NC1, NC2) activity.

Feature	Metric	C1	C2	SC1	SC2	NC1	NC2
1-Physical participation	Scalar	7	12	15	15	10	15
2- Number of utterances	Scalar	28	9	4	5	0	4
3-Talking time	Seconds	19.4	17	7.5	8	0	5
4-Number of talking participants	0, 1, 2 or 3	3	3	2	3	0	1
5-Talking time dispersion	Gini coeff.	.510	.284	.747	.60	1	1
6-Verbal participation dispersion	Gini coeff.	.357	.143	.75	.614	1	1
7-Physical participation dispersion	Gini coeff.	.875	.583	.533	.40	.2	.8

In this way, we obtained three different datasets in which each instance corresponds to one block of log lines grouped in 30, 60 or 90 seconds blocks. Speech recognition was not used in the analysis. If there were reliable recognition of speech, this might be fed into our approach. We used the Gini coefficient (Thomas et al., 2000) as an indicator of dispersion of participation as it has been successfully used to estimate equity of participation of students in learning environments (Belgiorno et al., 2010) and also for measuring levels of participation at multi touch devices (Harris et al., 2009). The Gini Coefficient ( $G$ ) is an indicator of statistical dispersion that ranges between 0 and 1. A coefficient value of 1 indicates total asymmetry or dispersion and 0 indicates total symmetry or perfect equality. This indicator can be defined as the mean of the difference between every pair of participants ( $n = 3$  or  $4$  in this study), divided by the mean size  $\mu$ . The formula we used to obtain the Gini coefficient is as follows:

$$G = \frac{\sum_{i=1}^n \sum_{j=1}^n |x_i - x_j|}{2 n^2 \mu}$$

#### 4.2.4. Evaluation

We created classification models based on the three datasets described above. We used the Best-First tree, C4.5 decision tree, Bayes-Net and naïve Bayes algorithms. The models were evaluated using two methodologies: 10x 10-fold Cross Validation (CV) and Leave-one-group-out CV. The 10 runs of 10-fold CV were performed on each of the 3 datasets for each algorithm. This is equivalent to breaking the data into 10 sets of same size, training on 9 of them and testing on the 10th, repeating this 10 times (folds) and repeating the whole process also 10 times. We used a standard baseline for comparing the performance of the classifiers. The *baseline classifier* simply takes account of the distribution of the frequency of the three possible label values.

We obtained results that are significantly higher than the standard baseline (Table 4-3). In general, even when the accuracy of the models is above our baseline we obtained sub-optimal performance with all the algorithms to predict *somewhat collaborative situations* (SC row). Our training dataset formed by blocks of 30 seconds produced some of the higher performance rates across the datasets (68% for naïve Bayes, 66% for Best-First tree and Bayes-Net of F-score), and it is more balanced in the prediction of the 3 possible values. For the second dataset, we got lower rates of performance compared with the others.

Table 4-3 Results of the 10-fold cross validation. F1=Balanced F-score, C= F-measure of the algorithm in classifying “collaborative” SC=somewhat collaborative, or NC= non-collaborative situations. EX= extreme misclassifications accuracy, OP= optimistic accuracy. BL=baseline, BNet= Bayesian Network, NB= naïve Bayes, BFT= Best-first tree, C4.5= C4.5 tree.

Log sets of 30 seconds						Log sets of 60 seconds					Log sets of 90 seconds				
	BL	BNet	NB	C4.5	BFT	BL	BNet	NB	C4.5	BFT	BL	BNet	NB	C4.5	BFT
<b>F1</b>	.34	.66	.68	.63	.66	.36	.66	.69	.64	.65	.36	.67	.62	.69	.68
<b>C</b>	.31	.70	.71	.65	.66	.46	.83	.86	.77	.82	.34	.77	.83	.66	.59
<b>SC</b>	.33	.56	.58	.63	.57	.22	.18	.22	.37	.25	.43	.50	.41	.70	.72
<b>NC</b>	.37	.73	.79	.74	.72	.33	.787	.72	.65	.69	.25	.81	.71	.71	.74
<b>AC</b>		.65	.69	.63	.66		.67	.72	.65	.70		.76	.72	.75	.73
<b>EX</b>	.28	.05	.08	.07	.06	.34	.45	.43	.47	.51	.27	.52	.54	.64	.65
<b>OP</b>	.82	.98	.98	.97	.98	.79	.85	.86	.83	.82	.83	.83	.80	.80	.79

The third dataset also produced high rates of correct predictions (F-score above .68 for the decision trees). However, an additional metric for gaining insights on the accuracy of the models was calculated. We call it *extreme misclassifications* (EX). It measures the proportion of incorrect classifications in which the *non-collaborative* blocks were misclassified as *collaborative* and vice versa. In educational terms, a *collaborative* block misclassified as *somewhat collaborative* is still giving information about the group activity. The proportion of extreme misclassifications for the 30 seconds dataset, for all the classifiers, stayed below 7.6%; therefore the results of these models are very promising. For the 90 seconds dataset, even when the accuracy levels are comparable to the first dataset, it does not perform well with the extreme misclassifications (highlighted row). The row

OP (Optimistic accuracy) shows what the accuracy levels would be if only extreme misclassifications are counted as errors. Whilst this is not ideal, it shows that the classifier model is very reliable. The algorithms which produce simpler models are the decision trees. Based on these we found that the features that best predict the classification are the number of utterances produced (at least 10 for a collaborative situation, 30 sec. dataset), low rates of verbal participation dispersion (Gini coefficient less than .40) and the absence of long periods of silence.

Table 4-4 summarises the results of the Leave-one group out CV. This analysis shows similar accuracy levels for each algorithm compared to the 10-fold CV but it also generates additional information regarding the performance of the models for each group. We noted above that the classifier algorithms produce more equilibrated results for the classification (C/SC/NC) using the 30 seconds blocks dataset. However, using a Leave one out approach on this dataset, we can see how the accuracy falls or rises depending on the group that is being tested each run.

Table 4-4 Results of the leave one out cross validation.

	Log sets of 30 seconds				Log sets of 60 seconds				Log sets of 90 seconds			
	BNet	NB	C4.5	BFT	BNet	NB	C4.5	BFT	BNet	NB	C4.5	BFT
Accuracy	.67	.69	.66	.65	0.66	0.69	0.66	0.67	0.65	0.64	0.61	0.61
Std. deviation	.10	.12	.14	.14	0.18	0.18	0.20	0.17	0.17	0.16	0.19	0.17
Correlation(C)	-0.10	-0.28	-0.21	-0.25	0.03	-0.14	-0.10	0.16	-0.32	-0.09	-0.30	-0.19
Correlation (SC)	-0.61	-0.79	-0.34	-0.38	-0.62	-0.69	-0.42	-0.30	-0.70	-0.55	-0.78	-0.55
Correlation (NC)	0.41	0.65	0.34	0.39	0.33	0.49	0.31	0.05	0.62	0.40	0.65	0.45

The Bayesian algorithms (at least the Bayesian network) have less oscillation in the classifications in the 30 seconds dataset (SD = 9.9%) compared with the decision trees algorithms (SD = 14% and 13.5%). We analysed the correlation between the proportion of collaborative periods and how well each model performs (accuracy). We expect not to have high correlation between the accuracy and the proportion of collaborative periods. In Table 4-4 we can see that the negative correlation increases for the SC blocks (below -.550 for Bayes-Net and naïve Bayes in all datasets). In other words, both Bayesian algorithms are good when groups clearly behave as very collaborative or non-collaborative and decrease in power for somewhat collaborative groups. In this same respect the trees performs “better” (corr. of -.34 and -.38 for the 30 sec. dataset) but their power of prediction oscillates more across groups (higher SD). We can then confirm that it is possible to infer when a group of people is in a collaborative situation, relying on the application and audio traces, taking into consideration the limitations of each algorithm. Even when our model only considers quantitative data we could get enough information to infer if learners were potentially engaged in collaborative interactions.

## 4.2.5. Section Summary

This study focused on inferring the extent of collaboration within groups of learners building on collaborative learning theories (Dillenbourg, 1998) and supervised data mining techniques. The aim was to explore the intersection between the quantitative traces of peer’s interactions and the research area of collaborative learning. The approach did not take into account the group’s performance because we did not find any relationship between collaboration and this feature, obtaining a correlation of -0.052. The main indicators of collaboration were the quantity and heterogeneity of verbal participation. However, the quantitative data does not tell the whole story of a group. **The performance of the classifiers to infer the extent of collaboration is good enough to provide valuable information which is currently not automatically available.** It would give teachers some indication of how well each group was collaborating. Different ways to visualise and implement these mechanisms will be discussed in the next chapters. The preliminary results of this study were promising and further research is needed to assess if they apply to other domains.



## 4.3. Modelling Symmetry as an Indicator of Collaboration

Similarly to the first study, the approach of the second study consists of exploiting the digital and audio footprints of the user's activity at collocated settings but this time to automatically build a model of symmetry of activity and extend it to tabletop environments<sup>1</sup>. This study describes a theoretical model of collaborative learning based on indicators of symmetry of activity and ways to implement it. The Gini coefficient is used as a statistical indicator of symmetry of activity, which is itself an important indicator of collaboration. This model was built from a small-scale qualitative study based on concept mapping at an interactive tabletop. The model was then validated using the larger scale corpus of coded data from the multi-display groupware presented in the previous study (Section 4.2). The key contributions of this second study are the model of symmetry of activity as a foundation for modelling collaboration which should have egalitarian participation; and the operationalisation of the model and validation of the approach on both a small scale study and a larger scale corpus of data. This study will be referred as *Study Waterloo 2*.

### 4.3.1. Motivation

Previous work in user modelling has articulated the importance of capturing a user model of learner's interactions in order to adapt and improve the support to the group activities in tabletop settings (Martin and Haya, 2010). Drawing on the collaborative learning theories (Dillenbourg, 1998; Stahl, 2009) described in Section 3.4, a useful indicator of collaboration is the notion of *symmetry*. This second study builds upon that work, to create a theoretical model of *symmetry of activity* of small groups in collocated settings, extended to interactive tabletops. The argument to be validated in this study is that the measure of the symmetry of participation (or activity) of collocated group members can provide insights into the extent and quality of collaboration of the groups, and that this measure can be extracted automatically from logs and audio traces.

Dillenbourg (1998) remarked on the importance of high levels of *symmetry of action*, *knowledge* and *status* for successful collaboration in learning contexts. *Symmetry of action* is the degree to which users perform the same level of activity. *Symmetry of knowledge* refers to the extent to which users have the same level of skills and knowledge. Finally the *symmetry of status* is associated with the relative position that each user has in their community. This study investigates whether assessing key aspects of the *symmetry of action* can determine important aspects of collaboration in the group when they share *symmetric knowledge* about the subject matter. Key features of this symmetry can easily be captured, whereas the symmetry of knowledge is highly domain dependent and therefore difficult to assess in a generic way. Similarly, the symmetry of status is a complex social phenomenon that cannot be tackled from a quantitative perspective.

We collected data from two sources: the logs of interactions (touches on an interactive tabletop or clicks in a multi-display setting, such as the one presented Study Waterloo 1), captured directly from the learning application; and the audio traces, obtained through wearable microphones. From these two sources of data, four measures of action were identified to model the degree of symmetry of activity: the equality and total duration of verbal interventions, and the equality and amount of physical interaction with the system. The methodology followed in this study consists of, first, conducting an exploration in a small study to define a model of group collaboration based on these measures, and then, evaluating this model through a large-scale study.

### 4.3.2. Context of the Study

An exploratory case study on a multi-touch tabletop interface was designed. Groups were recruited for the first part of the analysis to build an artefact collaboratively at the tabletop using a prototype, as shown in Figure 4-6. This prototype is a preliminary version of our tabletop application designed

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<sup>1</sup> Parts of this section have been published in the proceedings of UMAP 2011 (Martinez-Maldonado et al., 2011c).

for collaborative *concept mapping* (Novak, 1990). The further and complete implementation of this learning interface is fully described in the next chapter and used in other larger studies in the rest of the thesis. In this section we present a broad description of this prototype and an early implementation of its connectivity with other learning systems.

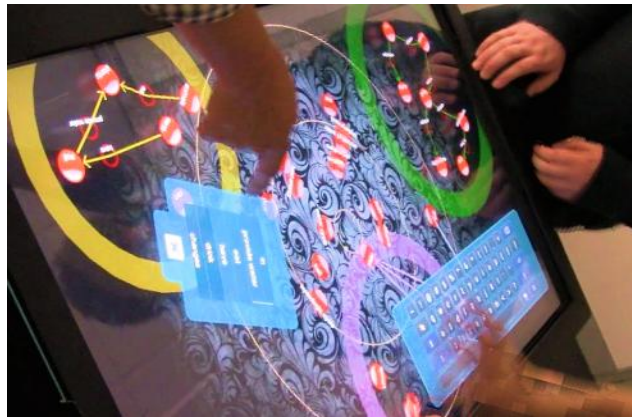


Figure 4-6 The tabletop application prototype being used to build group concept maps.

#### *The task.*

In the first part of the experiment, participants were asked to create an individual concept map, capturing their own understanding of a topic using their own concept set. After studying the same text titled: *Recycling, cost-benefit analysis*, participants were requested to draw maps answering the focus question: *does recycling help the environment?* These initial individual artefacts were built on desktop computers, and manually preloaded into the tabletop. In the second (and collaborative) part of the experiment, each group was asked to build a common group concept map at the tabletop. After the group had discussed their individual maps, participants could use the tabletop application to perform basic actions such as adding concepts, creating directed links between two concepts, moving, editing or deleting concepts and links.

#### *Participants and data collection.*

Every touch on the tabletop was logged, along with the user who made it, and all sessions were video recorded. In this exploratory study, there was no way to automatically associate each touch with the student who performed it. The solution consisted of providing each student with personal circular interactive areas that each had to move over the elements on the tabletop to be able to interact with them (see the coloured circular areas in Figure 4-6). As discussed in Section 2.3.2, these kinds of solutions where students are forced to follow certain behaviour to ensure touch identification at the tabletop are not ideal. For this study, this method proved to be helpful as a proof of concept of the type of data that needs to be captured, the challenges to record them and the importance of a pervasive solution to sense aspects of learner's actions. Sound was recorded with individual microphones worn by each participant. The study involved five groups, each of 3 or 4 participants, for a total of 18 participants. They were predominantly enrolled in engineering courses and were aged between 20 and 27. Group members were familiar with one another. Each group had thirty minutes to build the concept map. Groups performed between 1450 and 2360 actions per session, for 8500 recorded touches. We also obtained a total of 6296 seconds of active verbal participation that were manually extracted from the individual recorded tracks.

Table 4-5 shows 2 example excerpts from group logs. The fragment at the left corresponds to a collaborative group where students combined talking with actions at the tabletop, dedicating some time to discussion before making changes. An excerpt of a different group, that was, by contrast, not very collaborative, is shown at the right; this group dedicated most of the time to perform physical actions rather than discussing their ideas. Both fragments were extracted from the starting part of their respective sessions to illustrate the nature of the available data. These data are very similar to that collected in the multi-display setting described in previous section (Section 4.2.2).



Table 4-5 Simplified fragments of the combined logs (application + audio). Left: collaborative group. Right: Non-collaborative group. Results of the leave one out cross validation.

Collaborative group			Non-collaborative group		
Author	Time	Log	Author	Time	Log
2	5:59:13	audio participation 4 sec	4	2:49:06	app "add concept" 32 "production"
1	5:59:15	audio participation 4 sec	4	2:49:07	app "move concept" 32 "production"
4	5:59:16	audio participation 1 sec	2	2:49:06	app "scroll menu m44
1	5:59:18	app "scroll menu" m9	3	2:49:10	app "move concept" 32 "production"
3	5:59:18	app "move menu" m10	3	2:49:15	app "add concept" 33 "consumption"
4	5:59:19	app "add link" 1 "waste"	4	2:49:16	app "delete concept" 32 "production"
1	5:59:20	app "scroll menu" m10	3	2:49:16	app "move concept" 33 "consumption"
3	5:59:24	app "scroll menu" m11	2	2:49:17	app "scroll menu m44
4	5:59:29	audio participation 2 sec	2	2:49:18	app "add link" 35 "is"
3	5:59:31	app "move menu" m11	3	2:49:20	audio participation 1 sec
4	5:59:35	audio participation 2 sec	4	2:49:21	audio participation 2 sec
3	5:59:36	app "add concept gesture" m12	3	2:49:26	app "edit concept" 33 "consumption"

### 4.3.3. Model of Symmetry as an Indicator of Collaboration

Before any quantitative analysis was performed, the data and video recordings were examined to see whether any simple statistics could discriminate symmetric groups in terms of their collaborative behaviour. It was observed that a couple of groups were highly collaborative. They were distinguished from others in terms of their consistent verbal communication and awareness of other's physical actions, discussing most of the actions each group member intended to perform. The other three groups showed behaviours that ranged from periods of collaboration to periods of partial or non-existent communication. Most of the time, these participants worked individually, either not communicating with others or involving just a couple of participants in the discussion, leaving others working independently with the tabletop interface in a small region.

During the non-collaborative periods, participants split the work and worked in their personal space without awareness of others actions. These periods were characterised by high amounts of physical activity with each participant performing a similar number of actions, but low levels of verbal communication in very irregular amounts. This means that the Gini coefficient is expected in these cases to be quite low (reflecting symmetry) for the physical dimension whereas in the audio dimension it should be higher (reflecting asymmetry). By contrast, the collaborative periods were mostly characterised by high levels of verbal communication with a rather egalitarian distribution of participation in this dimension (hence a low Gini coefficient). However, as students were focused on the discussion and observing their peer's actions, the level of physical actions was lower compared with the non-collaborative groups. Additionally, it was observed that in some groups participants were keen to partially collaborate, leaving one or two members as spectators, or, at the extreme, one participant tended to do all the work by himself (hence a high Gini coefficient).

Table 4-6 shows the quantitative information corresponding to the metrics that this approach is evaluating, as indicators of symmetry, for 6 periods of group work. These metrics are: talking time, Gini coefficient of verbal participation, number of touches and the Gini coefficient of the quantity of touches. Columns 1, 2 and 3 of Table 4-6 shows information of three selected blocks of activity of a very collaborative group that reflect the higher levels of symmetric speech and lower and asymmetric levels of physical actions when compared with the other three selected episodes from a not very collaborative group (columns 4, 5 and 6).

Table 4-6 Tabletop data log grouped in pieces of 90 seconds.

Attribute	Collaborative group			Non-collaborative group		
	1	2	3	4	5	6
Radar #	1	2	3	4	5	6
$P_{talk}$ (seconds)	53	51	56	21	23	28
$G_{talk}$ (Gini coeff.)	0.131	.132	0.315	0.400	0.129	0.347
$P_{physical}$ (touches)	17	24	25	72	69	47
$G_{physical}$ (Gini coeff.)	0.488	0.678	0.587	0.214	0.357	0.242

Our observations led us to expect that our metrics of symmetry can model facets of the collaboration of the group. Based on the observations for this dataset, we hypothesise a set of rules, in terms of numeric metrics, as follows:

$$(low)P_{talk} + (high)G_{talk} + (high)P_{physical} + (low)G_{physical} \rightarrow \text{Non collaborative situations} \quad (1)$$

$$(high, medium)P_{talk} + (high)G_{talk} + (high)P_{physical} \rightarrow \text{Somewhat collaborative situations} \quad (2)$$

$$(high)P_{talk} + (low)G_{talk} + (low)P_{physical} + (high, med)G_{physical} \rightarrow \text{Collaborative situations} \quad (3)$$

where  $P_{talk}$  corresponds to verbal participation,  $P_{physical}$  to physical participation (touches, clicks),  $G_{talk}$  to the Gini coefficient as indicator of symmetry of talk and  $G_{physical}$  as an indicator of symmetry of physical actions. For example, according to the first rule (1), a possible non-collaborative situation would be characterised by low and asymmetric levels of verbal participation by group members, accompanied by higher levels of physical interactions with the technology that, would tend to be more symmetric since each student would be working by themselves. By contrast, an example collaborative situation would feature higher levels of talking and modest levels of physical interaction with the learning system.

After inspecting the correlation between these metrics of symmetry we found interesting relationships. There was a negative correlation between physical and verbal participation – corr. - 0.441, (see chart of Figure 4-7, left) and a stronger negative correlation between physical participation and the Gini coefficient of physical action - corr, -0.611 (Figure 4-7, right). In other words, when groups talk they do not perform many actions and, additionally, when they perform many actions, this physical activity is more egalitarian. However, in order to confirm that these observations are valid and useful across collocated domains, these rules were assessed in a second larger scale dataset based on a corpus of coded data.

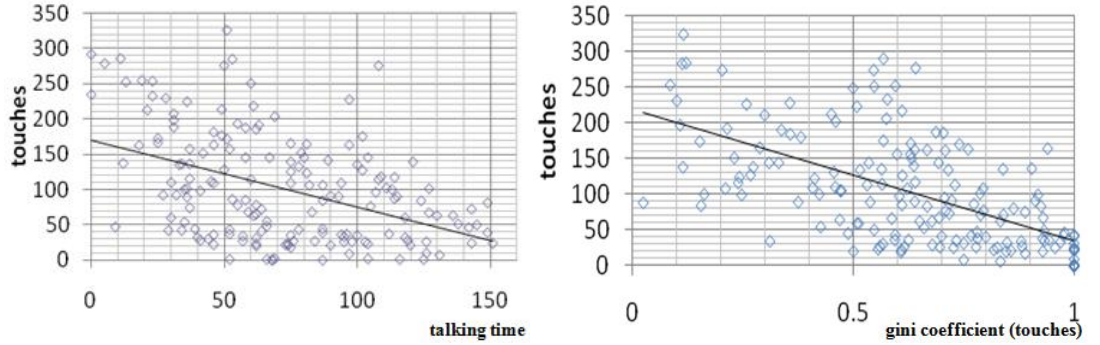


Figure 4-7 Left: Scatter plot of physical and verbal participation. Right: Scatter plot of number and the Gini coefficient of physical participation.

#### 4.3.4. Evaluation of the Model of Symmetry: Clustering Groups

We evaluated the rules described in the previous subsection using a sub-set of the dataset used in Study Waterloo 1 (see Section 4.2.2). This corresponds to data that was captured from 19 groups performing a Job Shop Scheduling (JSS) task, an optimisation problem previously used for evaluating group interactions (Tan et al., 2008). In this case, groups performed between 100 and 600 actions per solution, for a total of 9800 recorded interactions with the JSS software. In addition to the application data, we also considered a total of 4836 transcribed utterances.

The audio and application log lines were grouped forming sets of log lines. Using the same tagging process as the one used for Study Waterloo 1, a label was assigned to each 90 seconds block of activity for each group. We chose this time frame size based on the observations made of the videos of the sessions in that study that showed that there is not a significant difference between block sizes of 30, 60 and 90 seconds when assessing episodes of collaboration.

Each block of activity was coded as corresponding to one of three possible values. The highest being a *collaborative block* (C), if all participants participated to some extent and they were aware of their peer's actions during such period of time. *Medium collaboration* (M), if one or two members of the group were unaware of their peer's actions and the group communication was partial. The lowest possible value, *non-collaborative block* (NC), was assigned if the group split the task, working separately without awareness of or communication with each other.

Then, we grouped the log lines and calculated the same attributes we used for the first dataset. In this case, the key difference is that each 90 seconds of activity block is labelled with a qualitative rating of collaboration. This additional information and the larger size of the dataset served to apply our unsupervised machine learning techniques and supervise the results to validate the hypotheses posed in the previous section.

#### *Clustering groups according to their collaboration and symmetry.*

We used a clustering machine learning technique to reveal the relationship between the rules of our model described in the previous section and the extent of collaboration of the groups. The features used were verbal participation ( $P_{talk}$ ), physical participation ( $P_{physical}$ , number of clicks) and Gini coefficients as indicators of symmetry of talk ( $G_{talk}$ ) and symmetry of physical actions ( $G_{physical}$ ). Clustering has been used in a collaborative learning setting, such as in (Anaya and Boticario, 2009), where the authors aimed at grouping students according to their individual collaboration within their groups. In contrast, in our study clustering is used to assess whether our rules can be applied to other domains with the aim of obtaining meaningful information about the symmetry and collaboration of collocated groups.

We applied the clustering algorithm k-means with Euclidean distance measure. This algorithm is simple and effective if the number of clusters is previously known. However, k-means is sensitive to the initial seed. Therefore, to mitigate this limitation we ran k-means 10 times using the 4 attributes specified in the rules of our model. Additionally, we also ran a secondary algorithm, the Expectation Maximisation (EM), using the same settings (k=3 clusters and the same dataset), obtaining similar results as with k-means (see Table 4-7).

Table 4-7 Clustering results. Cluster-0 (C), Cluster-1 (M), Cluster-2 (NC).

Attribute	Clusters running 10 times k means				Clusters running EM			
	Full data	Cluster-0	Cluster-1	Cluster-2	Full data	Cluster-0	Cluster-1	Cluster-2
$P_{talk}$	28.67	32.52 (h)	35.00 (h)	17.23 (l)	28.67	29.72 (h)	37.10 (h)	11.23 (l)
$G_{talk}$	0.53	0.36 (l)	0.61 (h)	0.69 (h)	0.53	0.44 (l)	0.59 (m)	0.75 (h)
$P_{physical}$	36.7	33.79(l)	30.70 (l)	46.25 (h)	36.70	37.69 (1)	27.74 (l)	47.46 (h)
$G_{physical}$	0.35	0.31(m)	0.53 (h)	0.25 (l)	0.35	0.27 (l)	0.59 (h)	0.28 (l)

After the clusters from both algorithms were obtained, we compared the presence of collaborative, non- collaborative or moderately collaborative blocks in each cluster. The results of this comparison defined cluster 0 as the group with more collaborative blocks, cluster 1 as medium collaboration blocks and cluster 2 with the non collaborative blocks. The percentage of correct grouping was around 60% for both algorithms. This indicates that our clusters are not excellent classifiers but classification is not the purpose of our approach this time.

The comparison of Table 4-7 with the rules defined in section 4.3.3 revealed that every cluster formed by the second dataset followed similar numerical behaviour to the tabletop dataset. The rules presented in the previous section are defined in non numerical terms (high, low, medium levels of participation and Gini coefficients). For the Gini coefficient attributes ( $G_{talk}$  and  $G_{physical}$ ) the qualitative labels *low* and *high* can be translated into the quantitative equivalences *below 0.5* (more symmetric) and *above 0.5* (less symmetric). But for the numerical attributes ( $P_{talk}$  and  $P_{physical}$ ) the parameter to define the terms *low* and *high* are the corresponding average of the attributes across the complete dataset ( $P_{talk}=28.668$ , and  $P_{physical}= 36.714$ , see columns *Full data* in Table 4-7).

Rule: (low) $P_{talk}$  + (high) $G_{talk}$  + (high) $P_{physical}$  + (low) $G_{physical}$  → Non Collaborative situations.

We found that all parts of the rule are confirmed by the clustering information obtained from the two algorithms (see columns *Cluster-2*, Table 4-7). The non collaborative situations are characterised by a low level of talk, asymmetry in the conversation and high levels of physical action compared with the average across groups. Therefore, we can accept the rule hypothesised above.

Rule: (high, medium) $P_{talk}$  + (high) $G_{talk}$  + (high) $P_{physical}$  → Somewhat collaborative situations

It is not easy to define when a group is collaborating, even if experts directly observe the activity of groups. We observed that when a somewhat collaborative situation within the group exists it is because one or two members “lead” the activity in both physical and verbal participation. However, even when the clustering results for this type of partial collaboration (see columns *Cluster-1*, Table 4-7) show high levels of asymmetric verbal participation, it is hard to define what happened with the physical dimension, obtaining low level of physical actions and undefined symmetry ( $G_{physical}$  around exactly 0.5). Therefore, we cannot accept this second rule.

Rule: (high) $P_{talk}$  + (low) $G_{talk}$  + (low) $P_{physical}$  + (high, med) $G_{physical}$  → Collaborative situations

In this case the major part of the rule is confirmed by the clustering information obtained from the two algorithms (see columns *Cluster-0*, Table 4-7). The collaborative situations are characterised by high levels of symmetric conversation and less physical actions compared with the average across groups. We were expecting more asymmetry in the physical actions caused by the variable flux of the conversation. We learnt from this rule that collaborative periods tend to also be symmetrical in the physical layer. Thus, we can accept this third rule.

### 4.3.5. Section Summary

This section presented an exploratory approach to validate the significance of the notion of symmetry of activity for modelling collaboration within small groups. We generated a rule-based model based on a small-scale qualitative study at the tabletop. Then, the model was validated in a different context and learning situation: a larger dataset of collocated interactions. This approach applies qualitative assessment, statistical analysis for the formulation of the model and clustering techniques for the evaluation. **The evaluation demonstrates that both the amount and symmetry of verbal and physical participation are good indicators of collaborative and non-collaborative periods. The symmetry of participation is just one dimension of the complex collaborative process;** however, it provides useful information that would be an essential part of the group model.

## 4.4. Mining Patterns that Distinguish High from Low Collaboration

As was learnt from the previous two studies, electronic traces of activity have the potential to be an invaluable source to produce simple indicators of student’s collaboration around a shared device. This third study presents a data mining approach that exploits the log traces of a problem-solving tabletop application to extract patterns of activity in order to shed light on the strategies followed by learners<sup>1</sup>. The objective of this data mining task is to discover which frequent sequences of actions differentiate high achieving from low achieving groups. An important challenge is to interpret the raw log traces, taking user identification into account, and pre-process this data to make it suitable for discovering meaningful patterns of interaction. We compare two methods for mining sequential patterns by evaluating the information that they each discover about groups’ strategies. The key contributions of this study include the design of a novel approach to find frequent sequential patterns from multiuser co-located settings, the evaluation of the two methods, and the analysis of the results obtained mining. This study was the first research exploration that applied Data Mining

<sup>1</sup> Parts of this section have been published in the proceedings of EDM 2011 (Martinez-Maldonado et al., 2011f).

techniques in data collected from interactive tabletops (Martinez-Maldonado et al., 2011f). This study was carried out in collaboration with researchers of the University of Newcastle (UK), using their data. The abbreviation for this study will be *Study Newcastle* for further reference in the thesis.

#### 4.4.1. Motivation

This study reports our work in the context of Digital Mysteries (Kharrufa et al., 2010), a tabletop collaborative learning tool for the development of student's problem-solving skills. When using this tool, students have to examine the information they are provided with and formulate an answer to a posed question (the mystery). The student's cognitive processes become evident through their physical manipulation of the information on the tabletop to solve the mystery and thus observable for researchers (Leat and Nichols, 2000). However, when a class of typical size (20 to 30 students) is divided into several small groups working in parallel, it is very difficult for facilitators to keep track of the learning processes followed by all the groups and they usually end up just looking at the final results. This is a problem as it means that the higher level strategies followed by groups are lost. The work described in this study addresses this problem by mining and analysing frequent sequences of activity and highlighting key differences between high and low achieving groups.

#### 4.4.2. Context of the Study and Data Exploration

Digital Mysteries is a collaborative learning tool for the development and assessment of student's higher level thinking skills (Kharrufa et al., 2010). The task provided to the students is to solve a mystery with an open question in any subject such as mathematics, history, or physics. Students are given the question and a number of data slips which may hold direct clues for solving the mystery, background information, or even red-herrings. They are asked to analyse these to formulate their answer to the question. Among the main design concepts behind the original paper-based mysteries tool (Leat and Nichols, 2000) is that the student's cognitive processes become evident through their physical manipulation of these data slips to solve the mystery.

Digital Mysteries divides the task of solving a mystery into *three stages* and provides a set of externalisation tools at each of these. i) For the first "*information gathering*" stage, users are provided with around 20-26 data slips. Initially, these slips are displayed in a minimised pictorial form to save space at the tabletop. Consequently, users have to expand them to read the contained clues (see Figure 4-8, right). ii) For the second "*grouping*" stage, students are provided with a tool for creating "named" groups of slips and they are asked to categorise the slips into meaningful groups. Students usually create groups in support of or against a particular claim, or groups containing information related to a particular person, topic, or event. Students move to the next stage after placing all the slips into a minimum of four named groups. iii) For the third and last "*sequencing and webbing*" stage, students are asked to use a sticky tape tool to build a branched structure that reflects cause-and-effect relations and time sequences embodying the student's answer to the question. After completing this stage, students are asked to write down their answer. Digital Mysteries was implemented using a prototype of the multi-pen horizontal Promethean Activboard. Using a pen-based tabletop makes it possible to identify the author of each action. In this way, Digital Mysteries captures a rich set of interaction data throughout the mystery solution process that includes user identification or authorship as we will refer to it in the rest of this section.

##### *Participants and data collection.*

Every action on the tabletop was logged and all sessions were video recorded. The study involved 18 participants, in 6 groups of 3 participants each (see Figure 4-8, left). Some of the groups solved more than one mystery, generating a total of 12 logged sessions. Participants were school students aged between 11 and 14 years. Each group was asked to find the answer to a mystery. They had to read and understand the clues, cluster them into meaningful groups, discuss which clues were related to each other and formalise a response to the mystery. Triads performed between 970 and 2017 actions per session, for a total of 17130 logged actions.

*Data exploration.*

The raw data was coded as a series of Events, where Event= {Time, Author, Action, Object}. The possible actions that can be performed on the data slips are: moving (M), enlarging to maximum size (E), resizing to medium size (N), shrinking (S), Rotating (M), making unions with other data slips (U), add data slip to a group (G) and remove a data slip from a group (R). Out of the 12 sessions, 5 were coded as low achieving groups of students, 5 as high achieving groups and 2 as average. The level of achievement was coded considering: the quality of the discussions, the degree of logic thinking and the soundness of the justification for the solution of the mystery. A full report of this analysis can be found in (Kharrufa, 2010). The study presented in this thesis now focuses on the 10 groups *that clearly showed evidence of either high or low achievement*.

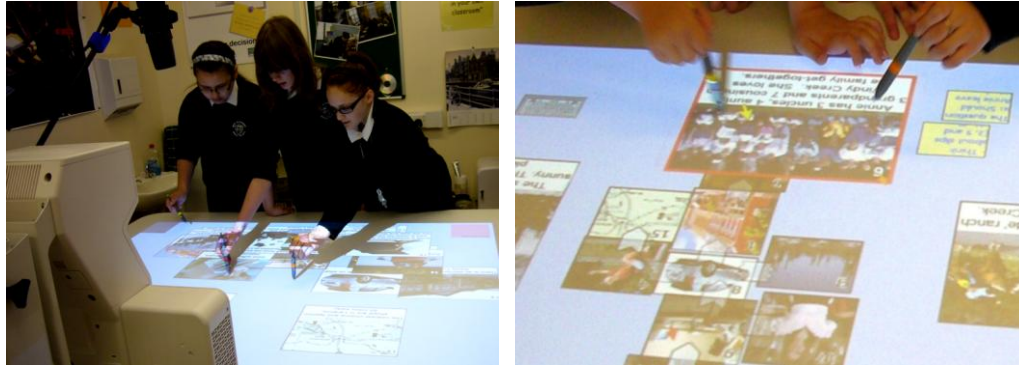


Figure 4-8 Digital Mysteries. Left: Three children solving a Digital Mystery. Right: Participants reading a clue.

#### 4.4.3. Mining and clustering sequential patterns

From a Data Mining perspective, the dataset collected from this co-located setting poses challenges for general data mining techniques. A first challenge is that there is a diversity of spontaneous actions that can be performed when using a tabletop as opposed to online systems, such as wikis or forums, in which learners have more time to think about their actions. As a result, the data might contain more non-relevant events. The second challenge is the special importance of the authorship of the low level events performed on Digital Mysteries. To address these issues we have set out to explore two research questions: i) what are the key insights that can be gained from raw and compact logged actions? (e.g. consider N similar actions as a group of actions rather than N individual actions), and ii) what information can be obtained by including authorship information in the post-processing stage of data mining?

The data mining task to solve is to discover sequences of interactions between group members and the data slips at the tabletop that were more frequent in high-achieving groups than in low-achieving ones, and vice-versa. Two important attributes of the data are the sequential order and, as mentioned above, the authorship. One technique that provides insights on the timing of the events is sequential pattern mining. A sequential pattern is a consecutive or non-consecutive ordered sub-set of a sequence of events (Jiang and Hamilton, 2003). However, as noted by Perera et.al. (2009), a frequent pattern of two actions X-Y might not be meaningful if many other events or large gaps of inactivity occur between such actions. This study focuses on the *consecutive* ordered sub-set of events that can potentially form a pattern. We will refer to these as *frequent sub-sequence sequential patterns*. Our algorithm seeks consecutive and also repeated patterns within the dataset of sequences. A generic flow diagram of our system is shown in Figure 4-9 (left).

The original *raw data* consists of the events performed at the tabletop, along with the authorship information of each of these events. A sample excerpt from a group session log is presented in Figure 4-9 (right). In Digital Mysteries each resource (data slip) provided to solve the mystery is present at the tabletop from the beginning to the end of the session. We took advantage of this to explore how learners interact with the resources at the tabletop. We first broke down each group's long and unique sequence of events into sub-sequences of actions per data-slip. Then, to

preserve meaningfulness in the patterns, we broke down these data slip's sub-sequences when a gap of inactivity longer to 120 seconds was detected.

We describe the above with a short scenario: the group decides to read a data-slip D and performs actions to enlarge it (move and enlarge actions), they read the data slip, close it and re-arrange it (more moves and shrink actions); if after this sequence there is a "group action" for the same data slip, but it occurs, say 5 minutes later, we can assume that the "group action" is not directly related to the previous actions. We chose a gap of 120 seconds as a maximum threshold beyond which the set of actions are considered as unrelated. This time frame was chosen based on the observations made of the videos of the sessions and the log files. In summary, the raw dataset we started with as input of step 1 is a dataset of 1618 sequences generated by breaking down the actions of each session in this order: by stage, resource (*data slip*) and long inactivity gap. The length of each sequence obtained was between 4 and 40 elements. In this dataset of sequences, each sequence is linked with the session, stage and resource it comes from. Each element within each sequence contains information on timing, authorship and action type.

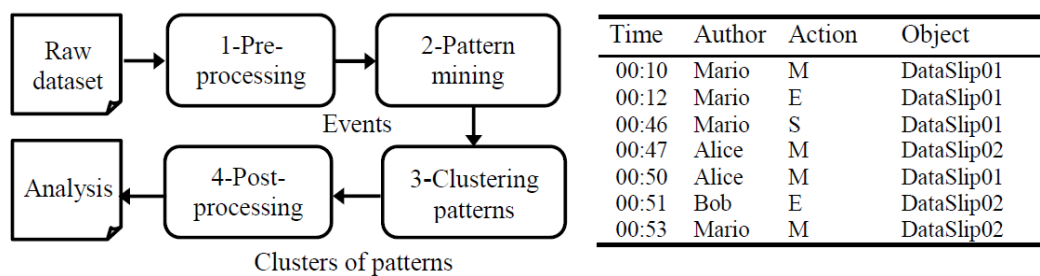


Figure 4-9 Left: Steps of our data mining approach. Right: Excerpt from the application logs of activity.

*Step 1.* We explored two pre-processing approaches: the first method consists of going straight into the sequential mining (hence a void step 1). The second method consists of compacting similar contiguous actions before applying the sequence mining. Both methods are described in detail in the next sub-section. The output of the first step for both cases is a pre-processed *dataset of sequences*.

*Step 2.* The *sequence mining* step is generic for both approaches. As mentioned above, our aim is to look for frequent ordered patterns within the action sequences. With the purpose of exploiting not just the frequency but also the redundancy of the patterns we are searching for, we chose an algorithm to extract the frequent sub-sequences from sequences using n-grams (Masataki and Sgisaka, 1996). An n-gram is a subsequence of n items from a given sequence. We set the minimum support threshold to consider a pattern as frequent if it was present in at least one quarter of the total number of data slips. We also set the maximum error of 1 to allow the matching of patterns with sub-sequences if there was an edit distance of 0 (perfect match) or 1 (one different action in the sub-sequence) between them. The output of this step is a list of frequent sequential patterns that meet the minimum given support.

*Step 3.* The purpose of step 3 is to cluster the patterns found in step 2. Indeed, without further treatment, patterns obtained from step 2 offer limited information to differentiate groups of learners. There can also be many similar patterns. As a result, it is tedious to analyse each pattern distribution across the groups. The patterns were clustered based on their *edit distance*. The edit distance between two patterns was defined as the minimum number of changes needed to convert one pattern of actions into the other, with the allowed operations: insertion, deletion, or substitution of a single action. We used a hierarchical agglomerative clustering technique (Witten and Frank, 1999) whose input is a matrix that contains all the edit distances between each pair of patterns. We chose this technique as it has proven successful in mining human-computer interaction data (Fern et al., 2010). The end result can be visually represented by a dendrogram, showing different levels in which patterns are clustered. These visual representations served to supervise the cluster formation and decide which level of clustering was considered as acceptable.

*Step 4. Post-processing and analysis.* We included the authorship information in the post-processing by considering the number of students who were involved in the patterns. We examined the benefits of the methods employed in step 1, i.e. the use of raw versus compacted data.

In next sub-section we describe in detail the specifications of each method and the results of the data mining outcomes in terms of collaborative learning.

#### 4.4.4. Method 1: Authorship in the post processing

The first method consists of exploring the information that can be obtained by mining the Human-Computer Interaction logs of physical actions without reducing the events.

##### *Pre-processing and sequence mining for method 1.*

The input data for the sequence mining (details in the previous section - 4.4.3) consisted of a list of sequential raw sequences of events (e.g. {M-E-M-M-S-M-N-G-S-M-R} where M=move, E=enlarge to maximum size, N=resize to normal size, G=add to group, S= shrink and R=remove from group). The output was a list of frequent patterns. Only sequences of at least 4 actions were considered. The final result included 259 frequent patterns of length varying from 4 to 10 actions.

##### *Post-processing and clustering for method 1.*

Based on direct observations made on the video recorded sessions and the sequential patterns found, we obtained many patterns that had a similar meaning, although the order or quantity of actions they contained were somewhat different. For example, the sequential patterns S1={M-E-M-M-S} and S2={M-M-M-E-S-M-M} (where M=move, E=enlarge, S=shrink) are both related to the same strategy: read a data-slip, close it and re-arrange it immediately afterwards (presumably to keep the interface organised and tidy). These observations led us to use clustering to group similar patterns. In this part of the process, the input for the hierarchical clustering algorithm was a similarity matrix of 259 x 259 that contained the edit distances of all pairs of sequences. The algorithm produced a dendrogram of 4 hierarchies as output. The clusters obtained were supervised to inspect the extent in which the groups were similar. After analysing the dendrogram, the second highest level was selected to form eight meaningful clusters. This is the only part of the approach in which the results were manually supervised.

##### *Results of method 1.*

We examined the results of the clustering by looking at the trends observed between patterns and groups of learners that presented a prominent level of achievement. We found that some sessions (high or low achievers) showed behaviour associated with certain clustered patterns. Therefore, we used unpaired two-tailed student t-tests ( $\alpha = 0.05$ ) to statistically analyse whether there were significant differences between such sessions. Table 4-8 summarises the clusters found using this approach and the results of such analysis.

Table 4-8 Clusters of patterns found by mining the raw events

Cluster	Example sequence	Favoured Groups	Participants
1- Read and arrange	{M-M-E-M-S-M}	Slightly more in high achievers	Both groups 1-2 authors
2- Read slip	{M-E-M-M}	Slightly more in low achievers	Both groups 1-2 authors
3- Arrangement	{M-M-S-M-M}	Substantially more in low achievers	Low achievers 2-3 authors
4- Ungroup	{M-R-M-G}	Slightly more in low achievers	Both groups 1-2 authors
5- Group	{M-N-M-G-M-S}	Both groups	Both groups 1-2 authors
6- Few unions	{M-M-U-M-M}	Substantially more in high achievers	Low achievers 2-3 authors
7- Moderate unions	{M-U-M-U-M-U}	Substantially more in low achievers	Low achievers 2-3 authors
8- Too many unions	{U-U-U-M-U-U-U}	Substantially more in low achievers	Low achievers 2-3 authors

The first two clusters are related to the strategies that learners followed to gather information from the data slips. Cluster 1 contained sequences linked with the strategy of reading the slips by enlarging the object and then, after a short time, closing them to keep the interface tidy. Some of



these groups positioned the slips in a certain region of the table to indicate they had already read them. On the other hand, Cluster 2 contained sequences of actions in which groups maximised the data slips without closing them. The observations on the videos indicated that some of the groups which followed this behaviour skipped the reading of some slips. We found that high achievers favoured the strategy of *reading, minimising and arranging immediately* (*cluster 1 mean = 124.75, cluster 2 mean = 61.25*). By contrast, low achievers used both strategies for the information gathering, performing more actions contained in Cluster 2 in which they did not close the slips immediately after reading (*cluster 1 mean = 104.40, cluster 2 mean = 114.80*). This simple change in the strategy for collecting information suggests that reading without re-arranging increases clutter, making the task more difficult to be controlled by the group. Indeed, cluster 3, which contains patterns for making space (moving and shrinking), showed a strong link with low achieving groups ( $t(8)=2.47, p=0.039$ ). As a result, low achievers spent much more time than the high achievers arranging the elements at the table.

Clusters 6, 7 and 8 contain “union” actions in which learners established links between the data slips they considered to be tightly related. Cluster 6 includes a sensible number of union actions (at most two unions) performed along with arrangement actions. Cluster 7 is for a moderate number of union actions. Cluster 8 presented patterns with an enormous number of union actions. Low achieving groups favoured clusters 7 and 8 ( $t(8)=2.97, p=0.018$  and  $t(8)=3.98, p=0.004$  respectively). Based on this trend, low achievers created too many unions related to a specific data slip in short periods of time. By contrast, high achieving groups favoured patterns with modest number of unions ( $t(8)=2.81, p=0.023$ ). Clusters 4 and 5 included patterns related to ungroup and group actions. In this case we obtained some differences among sessions. Low achievers made more “corrections” in categorising data slips than high achievers. In regard to authorship, we analysed the way in which participants collectively interacted with the resources in terms of number of authors involved with the data slip in each pattern.

For clusters 3, 6, 7 and 8 we obtained a strong statistical difference in the number of participants working together with the same data slip. Low achieving groups had more sequences in which the *three* authors performed actions sequentially compared with high achieving groups ( $p<0.05$  in all cases). For the rest of the clusters there were no significant differences in the number of authors involved with the patterns. For the clusters related to the strategies for gathering information (clusters 1 and 2) and grouping data-slips (clusters 4 and 5) the sequences were performed mostly by one author, and in some cases, by two authors in both high and low achieving groups (see Table 4-8, column Participants).

What can be learnt from these findings is that for students to have many hands on the same object at the same time does not imply improved work. In fact, the sequences in which the low achievers have the three participants involved are mostly for non-cognitively demanding tasks, such as arranging the elements on the tabletop (cluster 3). In the case of the “union actions” clusters (7 and 8) even when the activity is a cognitively demanding task, we learnt from the analysis described above and from observing the videos that lower achieving groups created a larger number of unions on particular slips that were not necessarily meaningful. From these results, and the video analysis, we can conclude that the high level groups worked more collaboratively and participants were keener to interact on one data slip at a time, even if they worked in parallel with different objects. We also explored the possible significant differences between the patterns and the stages in which they appear. As expected, clusters related to gathering information (clusters 1 and 2) are mainly in stage 1, cluster 3 (re-arrangement) with all the stages, Clusters 4 and 5 with stage 2 (grouping and ungrouping actions) and the clusters related to union actions are evidently for the third stage (sequencing and webbing). Thus, no further special analysis was done on the staging information.

#### 4.4.5. Method 2: Authorship in the post processing

The second approach consists of generalising (compacting). Then, we looked at the similarities of the outcomes of this method compared with method 1 results.

#### *Pre-processing and sequence mining for method 2.*

The dataset of sequences was compressed. The aim of the compression was to see how much information will be lost or gained if we generalised the user interface actions that can be attributed to user slips. A simple alphabet was applied which follows a single rule: the sequential actions of the same type (such as the action M in {M-M-M-E-M} or S in {S-U-U-U}) were compacted adding the quantifier for regular expressions + ({M+-E-M} and {S-U+}). The minimum length of the patterns was set to 3 actions, or 2 actions if at least one of the actions contained the quantifier +. In this case the minimum support was also set to one quarter of the data slips. The final result gave 261 frequent patterns of size between 3 and 5 actions each.

#### *Post-processing for method 2.*

The 261 patterns were clustered following the same process used in method 1. We obtained a dendrogram with 5 levels. The first issue found in this method was that patterns were more difficult to cluster accurately as they contained less contextual information (fewer items). The solution was to choose a lower clustering level and manually merge the smaller clusters which contained similar actions. Seven meaningful clusters resulted from the clustering supervision and also 2 extra very small clusters that could not be combined with any other cluster.

#### *Results of method 2.*

Even though some details in the sequences were lost, we found similar observable tendencies in the presence of patterns of high and low achieving sessions (see Table 4-9). This approach provided a deeper difference between the ways the higher and lower achieving groups gather information to solve the problem. For example we found a stronger difference in the strategy of reading without minimising the data slips performed mostly by the low achieving groups (Cluster 2,  $t(8) = 2.69$ ,  $p=0.027$ ). There was also a significant difference with respect to the strategy “read – close and arrange data slips” favouring the high achieving groups (Cluster 1,  $t(8)=3.05$ ,  $p=0.016$ ). Results also confirmed that low achieving groups created a huge number of unions between data slips in short periods of time (Cluster 7,  $t(6) = 3.05$ ,  $p=0.02$ ).

Table 4-9 Clusters of patterns found by mining *compacted* events.

Cluster	Example sequence	Favoured groups	Participants
1- Read and arrange	{M+-N-S-M+}	Substantially more in high achievers	Both groups 1-2 authors
2- Read slip	{M-E-M+}	Substantially more in low achievers	Both groups 1-2 authors
3- Arrangement	{M+-S-M+}	Slightly more in low achievers	Both groups 1-2 authors
4- Ungroup	{M-R-M+}	Both groups	Both groups 1-2 authors
5- Group	{M+-G-S}	Both groups	Low achievers 2-3 authors
6- Few unions	{M+-U-M-U}	Slightly more in high achievers	Low achievers 2-3 authors
7- Many unions	{M-U+-M-U+-M}	Substantially more in low achievers	Low achievers 2-3 authors

For the authoring information, the results from method 1 were also confirmed. The cluster that contains sequences with high numbers of union actions performed by 2 and 3 users at the same time were present mostly in the low achieving groups ( $t(8)=2.714$ ,  $p=0.027$ ). Some information is lost though; there were no significant differences between groups in any other aspect. In general, this approach confirmed the insights obtained applying method 1 but the quality of the results decreased in some cases.

## 4.4.6. Section Summary

**In this section we described a technique to mine frequent sequential patterns that distinguish high from low collaboration groups.** We were able to associate groups of similar patterns with collaborative strategies by applying clustering techniques. We addressed two questions through this third study, regarding (i) the key insights that can be acquired from mining raw or compact logged actions and (ii) the information offered by the authorship element of the data logs. We observed

that the results obtained with the two methods we applied reflected similar patterns of behaviour such as the strategies followed by the groups to gather information, arrange resources and the creation of links between data slips. Some elements of the interactions came up by compacting the redundant actions in method 2 (gathering information strategies), but in other elements some information was lost. The most important issue with the compacting method is that more empirical interpretation was needed after the clustering step whilst method 1 offered better clusters.

## 4.5. Insights, Considerations and Lessons Learnt

Overall, the preliminary studies highlight the high impact of the nature of student's data that can be available from a collocated setting on the type of questions that can be answered or the type of support that can be provided. The first two preliminary studies (Studies Waterloo 1 and 2) included the analysis of the utterances produced by group members. This information proved fundamental for the detection of levels of collaboration and for modelling collaborative learning. However, this raises implications for what information can be automatically captured by the learning environment. By contrast, the third exploratory study (Study Newcastle) proved that even when the verbal communication is not considered in the data analysis, the logged actions detected by an interactive tabletop can still provide insights on the strategies that differentiate high from low achieving groups.

Table 4-10 lists the lessons learnt from the three initial exploratory studies. This information complements the literature survey to provide a foundation for the implementation of the Conceptual Framework (TSCL-CF) presented in Chapter 3: our own learning tools, data capture systems (to be presented in Chapter 5) and the rest of the data analysis to be presented in the following chapters.

Table 4-10 Considerations about the feasibility and design requirements to build a solution to automatically analyse collaboration at face-to-face settings that were learnt from the exploratory studies.

Study	Lessons learnt
Study Waterloo 1	<ul style="list-style-type: none"> <li>Quantitative indicators of participation provide rich information that can help detect, to some extent, that a group may be engaged in either collaborative or non-collaborative situations.</li> <li>The inclusion of basic information of verbal participation enriches the models of face-to-face collaboration.</li> <li>It is possible to detect the degree of collaboration within a group of students, especially for extreme cases.</li> <li>Group of students that do not clearly behave as collaborative or non-collaborative groups are not easy to automatically be tagged by data mining techniques.</li> <li>Classification techniques proved effective in detecting periods of students' collaboration.</li> </ul>
Study Waterloo 2	<ul style="list-style-type: none"> <li>Simple rules of quantitative data can provide key indication of collaboration in both multi-display and single-display settings.</li> <li>Key (but not conclusive) indicators of collaborative learning are the amount and degree of symmetry of verbal participation.</li> <li>In some cases, there is a negative correlation between verbal and physical (touch or click input) participation.</li> <li>Rule-based group modelling and clustering techniques can be respectively used for proposing a simplified descriptor of possible behaviour and to supervise that these rules conform to students' behaviours across learning environments.</li> </ul>
Study Newcastle	<ul style="list-style-type: none"> <li>Data mining techniques can be applied to datasets collected from interactive tabletop learning applications to discover students' strategies.</li> <li>Automatic input differentiation is very important to be able to analyse students' strategies.</li> <li>Sequence mining techniques can be very useful to identify patterns of activity that can lead to differentiate groups according to their degree of achievement.</li> <li>Clustering techniques can be used as a second step in a data mining approach to group similar frequent sequences (obtained by applying sequence mining algorithms) and enhance the association of similar actions with higher level strategies followed by students.</li> <li>Logged actions can still provide valuable information on students' strategies even when information about students' speech is not available.</li> </ul>

The particular contributions of each study can be described as follows:

Study Waterloo 1 broke new ground on exploring the feasibility of applying data mining techniques to detect useful levels of face-to-face collaborative behaviour. This is especially useful for groups that clearly behave at the extremes of collaboration and non-collaboration. Even though the learning activity was not performed on interactive tabletops, this is an important contribution given that the actual observation of collaborative interaction can involve a high degree of complexity that is most commonly analysed through human observations.

Study Waterloo 2 proposed simple rules to help identify, to some extent, collaborative behaviours and that these rules apply for both multi-display and single-display face-to-face settings. The single display used in this study is a multi-touch tabletop; hence, the study introduces the applicability of the data exploration commenced in Study Waterloo 1 to tabletop-based learning settings.

Finally, Study Newcastle focuses on a tabletop learning environment where the information about differentiated student input is automatically and unobtrusively captured but the speech information is missing. In this way, the approach showed that even though verbal communication is important for this kind of analysis of collaboration, the physical activity on the tabletop interface can still provide valuable information about student's strategies.

## 4.6. Chapter summary

The three studies in this chapter are built upon educational data mining research. Different approaches were proposed as a starting point to guide future research on the identification of patterns from educational tabletop settings in particular, but that may be extended to other face-to-face computer-based learning scenarios. The rest of the thesis will show how we achieve our goal, to mirror useful information about groups so that this can help facilitators reflect on and improve the learning activity. Some of the principles and lessons learnt from these studies are put into practice in our own learning environments. Figure 4-10 shows the two main components of the Theoretical Foundation of the framework proposed in this thesis, namely the Literature review of Chapter 2 and the preliminary studies that were presented in this chapter.

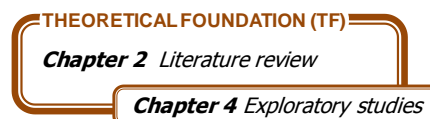


Figure 4-10 Elements of the Theoretical Foundation of the TSCL-CF

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## Chapter 5: Tabletop Software and Infrastructure: CMATE and COLLAID

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*"There can be infinite uses of new age technology, but if teachers themselves are not able to bring it into the classroom and make it work, then it fails"*  
-Nancy Kassebaum

**Summary:** This chapter describes the design process and implementation of our hardware and software infrastructure. The first element presented is a set of design guidelines for implementing a technological environment that allows 1) students to collaborate and learn; and 2) capture of student's interactions and their progress on the task. The second element is a learning environment that allows a group of students to decide on strategies to work collaboratively and build a concept map (CMATE). We present the iterative process we followed to design our tabletop concept mapping application, along with its usability features and their impact on collaboration. The third element that is explained is the design and implementation of a novel approach to automatically and unobtrusively capture the digital footprints of learners as they interact face-to-face at the tabletop (COLLAID).<sup>1</sup>

### 5.1. Introduction

This chapter is motivated by the next question: how can we build systems that consider, in the design phase, the ways in which interaction data can be captured for further analysis? **The goal of this chapter is to provide a description of the design guidelines and the technological implementation of an approach for capturing, formatting and processing student's interactions at a tabletop learning environment.** The purpose of the previous chapter was to highlight the possibilities and the feasibility of exploiting student's interaction data to find interesting patterns that can help either find evidence of effective collaboration or produce key indicators that distinguish groups that might need closer attention. In those examples, even though the learning environments provided limited possibilities to capture the rich information that can be generated from student's interactions, it was possible to explore the possibilities to use the data to perform further analysis of collaboration and group work.

Figure 5-1 shows the thesis goal that this chapter is addressing: the description of a series of design guidelines to implement the features of a system that unobtrusively captures traces of face-

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<sup>1</sup> Parts of this chapter have been published in international conference proceedings of ITS2010 (Martinez-Maldonado et al., 2010a), ITS2011 - Interactive Tabletops (Martinez-Maldonado et al., 2011b); at the international workshop ASTC held in UMAP2011 (Martinez-Maldonado et al., 2011a) and at the Work-In Progress track of CHI2012 (Ackad et al., 2012).

to-face collaboration at the tabletop. It also shows the two main contributions of this chapter, which are the instantiation of our design guidelines in the form of:

1. **CMATE**; a concept mapping tabletop application that allows students to freely decide the ways they interact and collaborate.
2. **COLLAID**; an enhanced tabletop-based system that captures differentiated student's touch interactions with the tabletop and speech participation;

The chapter describes the design process and the validation of these tools. For our learning environment (CMATE), we iteratively tested a number of prototypes to improve usability and collaboration support. We validate our data capturing environment (COLLAID) by evaluating the accuracy of the system to recognise different student's input. We additionally validate the feasibility of performing analysis of collaboration on student's data captured through COLLAID.

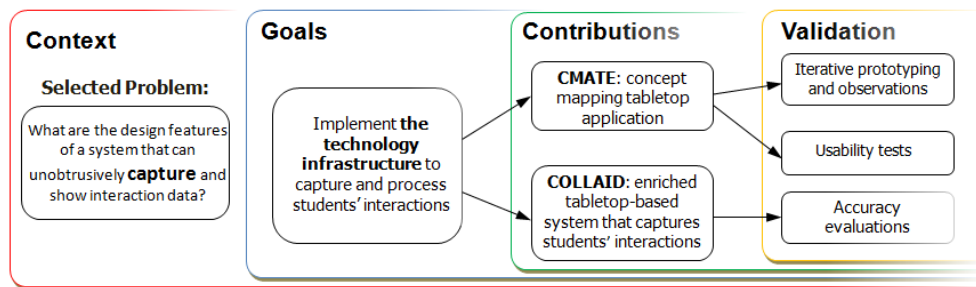


Figure 5-1 Context, goals, contributions and validation of Chapter 5.

This chapter also describes elements of the Data Capture Foundation (DCF) presented as a key component of the Tabletop-Supported Collaborative Learning - Conceptual Framework (TSCL-CF). Figure 5-2 shows the elements of the DCF that are addressed in this chapter. The Sensing System (SS) is implemented as COLLAID. It is a sensing system that enhances regular interactive tabletop hardware by adding user differentiation capabilities. Then, the host learning application, CMATE, performs basic pre-processing of the data captured by COLLAID. This application records the captured information creating activity logs, traces of communication, traces of the progress on the task and information about the group artefacts. A key element for the design and the implementation of the technological infrastructure is the Central Data Repository that allows the synchronisation and accessibility of the data to feed other services that can analyse and produce group indicators in *real-time* or for post-hoc reflection.

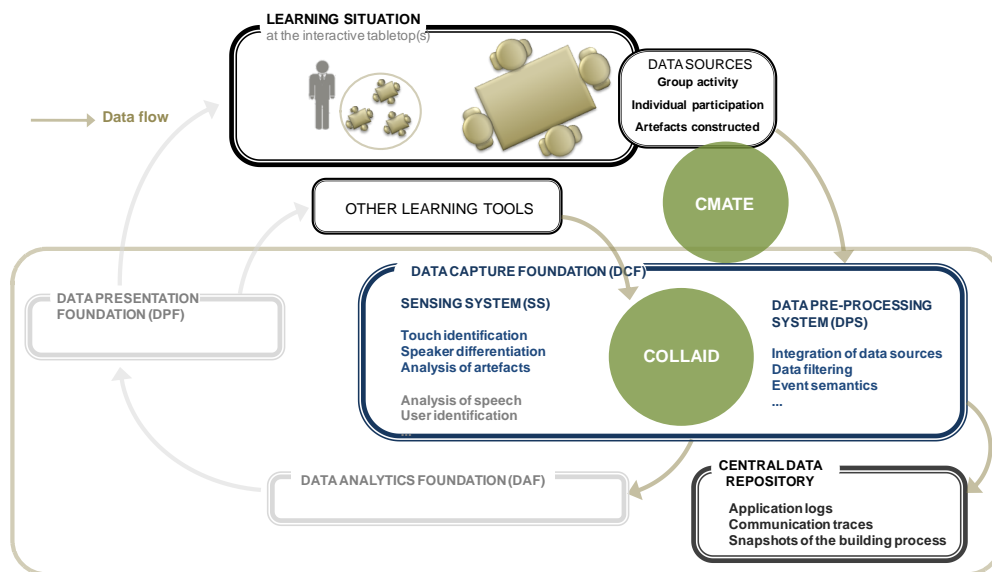


Figure 5-2 CMATE and COLLAID in context with the TSCL-CF.

This chapter is organised as follows. Section 5.2 presents the guidelines for designing face-to-face learning environments that can capture student's data to provide further support. Section 5.3 presents the learning environment (CMATE) and Section 5.4 describes the implementation of the data capture system (COLLAID).

## 5.2. Design Guidelines to Capture and Format Students Data

Research on user modelling has emphasised the potential of monitoring collaborative processes and using machine learning techniques to build tools that can make visible aspects of such learning process (Magnisalis et al., 2011). As described in Chapter 2, most of research in educational contexts has focused on the use of networked or e-learning tools (e.g. chat, forums, IM, email and other more complex environments). E-learning and face-to-face environments are not two entirely separate domains. Students are immersed in both experiences: virtual and real worlds. They interact via email or chat, but also have times in which they work face to face. Interactive tabletops can provide support during the periods when students have to create understanding in collocated settings.

Currently, there are many tabletop-based learning interfaces (see Section 2.3.3) but it is timely to establish principled guidelines to design the key features that should define these systems in terms of data capture, its analysis and the provision of support. Some very broad design guidelines for single-tabletop systems have been previously proposed. Scott et. al. (2003) established a set of high level guidelines for tabletop systems intended to support collaboration, mostly from an HCI perspective.. More recently, Nacenta et al. (2010) explored the impact of the interaction techniques and location of feedback on the way in which users collaborate. Kharrufa et. al. (2010) also investigated the design of tabletop applications focused on learning contexts. These authors describe the importance of grounding the design of educational tabletop applications on learning theories to increase the likelihood of students engaging effectively in collaborative discussions.

This section outlines a set of guidelines for this new area that can serve as a basis for designing interfaces for a range of collaborative tasks in a manner that will make it feasible to provide support for collaboration in the form of data visualisations, personalised capabilities or content delivery<sup>1</sup>. Figure 5-3 shows the elements of our approach. This starts by choosing suitable theories of small group collaboration, since they indicate the key elements of effective collaboration and learning (the Theoretical Foundation of the TSCL-CF, see Section 3.4). These theories should define the goals and drive the design of the collaborative setting and what information is required by the teachers or the research goals. For example, if a teacher decides that the measure of symmetry of participation is important, based on the definition given by Dillenbourg (1998), the system should be designed to capture elements that can provide differentiated learner's actions or contributions. This is needed to know who did what, and so to assess the level of participation of each learner.

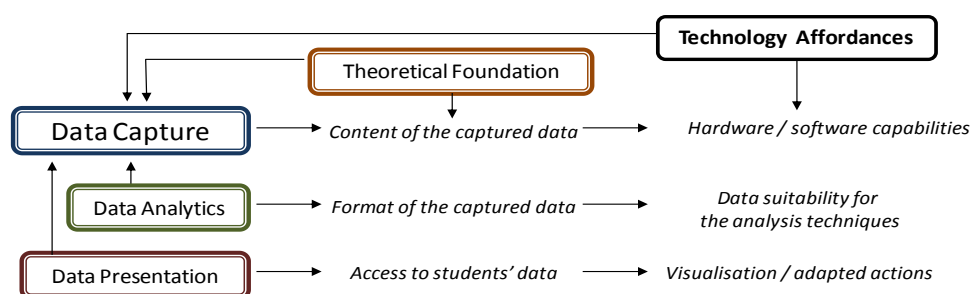


Figure 5-3 Aspects to consider in the design of supportive tabletop learning systems grounding on theories of collaboration, technology affordances, analytics tools and presentation needs.

However, even when these theories establish the ideal aims, the technology limitations can profoundly impact what is actually possible to capture and the associated cost to implement a

<sup>1</sup> Parts of this section have been published in the proceedings of the workshop ASTC held in UMAP2011 (Martinez-Maldonado et al., 2011a).

certain solution *in the wild*. Therefore, the content of the data can be circumscribed by the *affordances of current technology* (both hardware and software) to capture user's data (see Section 2.3.2 for related work). One example is that it may be desirable to perform automated transcription of what is said by each participant, but this still rises numerous challenges in authentic collaborative scenarios (Yu and Nakamura, 2010).

In the rest of this section we outline generic principles for capturing and mining data in tabletop-based learning systems. We present two sets of design guidelines. The first set presents the principles to collect student's data. The second set describes the considerations for formatting the data in a way that can be exploited using analytics techniques such as artificial intelligence approaches, data mining or statistical tools.

### 5.2.1. Principles for Capturing Students Data

Special attention should be given to the architecture of the tabletop-based setting to make the collection of data useful and successful. Next, we outline a set of key principles for designing tabletop-based systems that provide capture of student's data considering both the learning theories and technology affordances.

(i) *Distinguishing users (authorship of actions) and, if possible, identifying them.* One of the most important requirements for capturing rich contextual information and providing certain types of adaptation at the tabletop, is to distinguish between each user's touches (Martín and Haya, 2010). It is essential to know *who-touched-what* in order to perform a full data analysis of actions or to offer support in the form of personalisation and customisation of the interface. Current solutions for distinguishing who is touching the tabletop include specialised hardware, such as the DiamondTouch, attaching gadgets to user's hands (gloves or pens, see Section 2.3.2). Another option is to restrict user's reach by assigning roles or territories, and asking them to respect other's personal space (Morgan and Butler, 2009). However, this means that the task and user's behaviour are constrained to meet the user identification requirement. Either way, in order to provide advanced collaboration visualisation and analysis of possible patterns, it is required that the system supports user identification or, at least, user differentiation (refer to Section 2.3.2).

(ii) *Capture verbal communication.* The presence and content of the utterances made during collaboration are crucial for analysing collaboration (Dillenbourg, 1998), and tabletop settings should be instrumented to capture them. Previous work on tabletops has made use of the manual transcription of the utterances spoken by the group members (Fleck et al., 2009; Harris et al., 2009; Marshall et al., 2011; Tse et al., 2007) or the automatic collection of the presence of speech to measure levels of participation (Bachour et al., 2010). The captured speech can range from detecting when people are talking, to more detailed aspects such as the tone, volume or the speech content. The speech features of collocated learners can be captured using individual wearable audio recorders or less intrusive multi-directional microphone arrays.

(iii) *Integrating user and contextual data.* The model of the collaborators (that the tabletop can use to reason about the group's status) can be enhanced by incorporating information that is beyond the boundaries of the physical tabletop system. This information includes, for example, the degree of familiarity of group members, their individual learner models, outcomes reached in other academic activities (Mostow, 2004) and ubiquitous information like position or proximity to the table (Ballendat et al., 2010). If the tabletop is used as a part of a sequenced activity which involves other technologies, such as web-based portals or desktop multimedia, then a possible solution is to make use of a common user modelling framework (Kobsa, 2007) to integrate multiple services or to share data through a central repository.

(iv) *Integrating different services.* Tabletop applications should be designed so that they can be integrated within a larger scale system that can give continuing support to the learning process of the students. Current online e-learning and project management tools support asynchronous collaboration. Using tabletops as an added interface to existing collaborative e-learning tools, such as wikis, chat or forums, can expand the capabilities provided by these *input services* and improve



the collaborative experience by supporting face-to-face group work sessions. In this way, tabletop applications can be integrated within a larger scale system that can give continued support to the student's learning process over long periods (Paramythis and Mühlbacher, 2008). On the other hand, the information captured during the tabletop sessions should be available for *output services* that can exploit this information to improve the group member's awareness of collaboration.

(v) *Interconnecting with external devices.* Scott et. al. (2003) noted the importance of facilitating the transition between the collaborative work at the tabletop and external work performed through other devices. In collaborative situations, learners usually can make use of multiple sources of information, from books and paper articles, to modern devices like desktop computers, whiteboards and smart phones (Katherine, 2006). Personal devices and interactive surfaces other than tabletops provide added specialised functions and the flexibility needed for specific tasks. These are individual spaces in which learners can work first, and then they can share their individual work with the group. It is also important to record the user activity using these various devices to gather a comprehensive set of data about the group actions. To illustrate this point, consider a scenario in which a digital whiteboard is used to brainstorm ideas, with the results stored on a personal device, and shared at the tabletop for group discussion. In a classroom, multiple tabletops can be inter-connected or managed by a central service controlled by the teacher.

(vi) *Capturing audio/video information for deeper analysis (not real-time).* The analysis of peer communication is very important for analysing the collaborative processes and it should be instrumented in tabletop settings. The data that is useful to capture can be identified by drawing on the collaborative learning theories underpinning the system. It can include just the *presence* of voice to measure the verbal participation of learners or more detailed information like tone, volume or, as most learning theories state is crucial, the speech content (Dillenbourg, 1998). Detection of affective states in learners may also be considered by exploiting video and other sensor information (Calvo and D'Mello, 2010). The analysis of video and audio recordings require high amounts of time and effort but emerging technologies can extract key features that can provide interesting information about the processes of collaboration in face-to-face scenarios (McCowan et al., 2005).

### 5.2.2. Principles for Formatting and Mining Tabletop Data

Once the student data are collected, before starting to use analytics tools, these data should be transformed into a suitable format. In this sub-section, we propose a number of principles to facilitate the formatting of the data to meet the analytics requirements.

(vii) *Defining the degree of structure of the activity.* The interface may afford and constrain some activities to be performed at specific times according to a script. In this way, the logged data is naturally connected with the different steps of the collaborative process, hence aiding data interpretation. Furthermore, the design may help learners to collaborate – as a starting point – while they do not have their own coordination strategies (Weinberger et al., 2005). An example of this design approach was used by Kharrufa et. al. (2010) in which the tabletop activity was divided into three stages, providing users with different goals and tools in each of them.

(viii) *Capturing the data in multiple formats.* Another design aspect to consider is that data needs to be captured and recorded in multiple formats according to the potential analysis techniques that can be used to exploit it. This is important because different algorithms might require specific contextual information. For example, sequential pattern mining algorithms need data formatted as a detailed sequence of events. Other techniques might need the historical status of the objects at the tabletop to measure the progress on the task over time.

(ix) *Defining the logging semantics.* The lowest granularity at which the raw physical actions on the tabletop can be logged is the coordinates of each touch point. These data can be used to study low level dimensions of the group activity like territoriality or user interactions (Tang et al., 2010). However, this kind of logging does not indicate much about collaboration. Semantically meaningful data logs should be created to gain understanding of the strategies followed by groups (e.g. create an object; press a button; group elements). In addition, it might be valuable to establish even higher-

levels of abstraction by giving meaning to sets of basic actions based on heuristics. For example, basic actions, such as rotating elements towards others, can indicate communication (Kruger et al., 2004), or sequences of actions, such as dragging, inserting text or resizing, can be associated with higher level strategies like collecting information, brainstorming or negotiation.

(x) *Recording to a database.* As simple as it sounds, recording the logging information to a database is crucial, not only to make it easier to analyse the datasets after the activity has concluded, but also to allow support services to have access to student's data and present distilled information to teachers or students in *real-time*. If the logs are contained in files, then the opportunities for supporting students or generating visualisations of the group progress while they are still working are quite limited.

### 5.2.3. Section Summary

To design support tools in collocated settings where horizontal tabletops are present, it is crucial to establish the design principles required by these systems to capture, integrate and format student's data. **We discussed a number of guidelines that can serve as foundations to implement the infrastructure to build effective collaborative tabletop systems.** The next sections describe the implementation of our learning and student's data capturing systems.

## 5.3. CMATE: Collaborative Concept Mapping at the Tabletop

As discussed in Section 2.5, *concept mapping* is an important educational technique that provides an excellent means for a learner to externalise knowledge of a particular domain and to gain meaningful understanding of new information (Novak, 1995)<sup>1</sup>. Moreover, concept maps can be used as social artefacts through which students communicate their understanding (Roth and Roychoudhury, 1993). The spatial arrangement in concept maps allows for fast information retrieval (Hook and Börner, 2005), which can support social interaction. Several studies have reported that students who collaboratively generated concept maps achieved higher scores than those who constructed their concept maps individually (Okebukola, 1992; Okebukola and Jegede, 1989), and this helped students to integrate new information with previous theoretical knowledge (Cañas et al., 2003; Chaka, 2010; Preszler, 2004). When concept maps are generated collaboratively in dyads or groups, they become shared social artefacts that elicit existing and missing connections and spur discussion among students and teachers. Both concept maps and collaborative learning have been found to have educational benefits. Combining the two could produce synergistic beneficial effects.

Table 5-1 Limitations of previous concept mapping tabletop solutions.

System	Limitations
Tool to navigate through wiki content (Baraldi et al., 2006)	Single user application. Uni directional orientation.
Tabletop Mind-Mapping (Buisine et al., 2007)	Mind mapping tool
Concept mapping with tangibles (Tanenbaum and Antle, 2009)	Single user application Use of tangibles, limiting the size of the concept map Highly coupled to the tabletop hardware
Concept mapping using TinkerLamp (Do-Lenh et al., 2009)	Use pieces of paper, limiting the size of the map Uni directional orientation. Highly coupled to the tabletop hardware
Tabletop-Concept Mapping (Oppl and Stary, 2011)	Use of tangibles. limiting the size of the concept map Highly coupled to the tabletop hardware

Multi-touch tabletops appear to drive growing interest for designing collaborative concept mapping application because these devices can afford fluid interaction and improved access to

<sup>1</sup> Parts of this section have been published in the proceedings of ITS2010 (Martinez-Maldonado et al., 2010a), and ITS2011 (Martinez-Maldonado et al., 2011b).

information, important characteristics in educational contexts. This section describes CMATE, a tabletop collaborative concept mapping system. The construction of CMATE was motivated by the lack of multi-touch concept mapping tools that can provide collaboration support, regardless the hardware technology being used, and offer a degree of flexibility to connect to these learning environments, load concept maps in other formats, and connect to other systems such as sensing and awareness tools. Section 2.5.2 presented a number of other tabletop-based concept mapping applications. Table 5-1 outlines some of those which are either highly coupled to the hardware used by the designers/researchers or have poor affordances for collaborative learning.

### 5.3.1. Design Process

We present CMATE (*Concept Mapping at an Adaptive Tabletop for Education*), an interface designed to support learners by allowing them to compare personal and collective understanding captured in the form of concept maps. Our design and its evaluation draws on principles of concept mapping, rethinking the user interface to address the limitations and affordances of tabletops, to allow learners to focus on their core task of concept mapping. The design was also guided by user interface design heuristics: Nielsen's general usability heuristics (1994), heuristics for interactive tabletop software proposed by Apted et al. (2009) and specific guidelines for collaborative interactions at a tabletop described by Scott et al. (2003).

We illustrate the initial view of the use of CMATE with a scenario. Alice and Bob have just read a text, "Introduction to Living Things". They first each use a desktop concept mapping editor to create a personal concept map capturing their own understanding of the key ideas in the text. These personal concept maps are loaded into CMATE. This will serve two purposes: (i) to extract the vocabulary of concepts and links used in individual maps and make it available to the users, and (ii) to be able to highlight in the group map which concepts and links were present in each individual map. Alice and Bob then start using CMATE to create the collaborative concept map. For the collaborative activity of creating a combined concept map, CMATE starts with an empty map (or it can be preloaded with a basic scaffolding map). It presents concentric circles, which help learners lay out concepts at the levels that reflect the generality of the concepts. This design differs from the classic layout of concept maps, this is to account for the different orientation of users around the table. In CMATE, the most general concept should be placed in the centre, with more specific concepts placed around it. Each user is allocated a colour (e.g. orange for Alice and yellow for Bob). CMATE presents the elements added by each student with a different colour to help students easily see that the concept map, collaboratively constructed, integrates multiple individual contributions.

To achieve this vision we developed CMATE by employing an iterative design process. The design of the final version of CMATE extended for a total of two years. For brevity, we present the three major iterations of this process. Each iteration consisted of the following steps:

1. *Definition of CMATE's (new) features.* New features or corrected features for CMATE are listed. These are defined from the results of the user studies conducted in the previous iteration or on key principles of collaboration and concept mapping.
2. *Implementation of features.* After analysing the impact of the user interface features, mainly on collaborative learning aspects, these are implemented in the CMATE system or prototype.
3. *User studies (validation).* User studies were conducted for each iteration, with 3, 4 or 5 small groups of students with, 3 or 4 members each. Each student was questioned regarding the user interface (usability tests) and also requested to perform authentic group tasks in order to assess the effectiveness of the tool to support collaborative learning (Coppin et al., 2011).

Table 5-2 outlines those features that were introduced in each version and remained in the final version of CMATE. Some features were not included in the final version when there was little evidence that they could foster collaboration or they affected the usability of the system.

Table 5-2 Prototyping design process of CMATE.

Theoretical principles	Introduced features	Features that did not show evidence of usefulness:
Prototype 1 Figure 5-4	<ul style="list-style-type: none"> <li>-Basic concept mapping editing options.</li> <li>-Each student is associated with one colour.</li> <li>-Each element is colour coded.</li> <li>-Use of a black hole to delete elements.</li> <li>-Use of virtual keyboards for editing text.</li> </ul>	<ul style="list-style-type: none"> <li>-Highlighting <i>all</i> the parts of the map created by specific users (Figure 5-5).</li> <li>-Users had to explicitly indicate who did what by pressing a button and taking turns to perform actions.</li> </ul>
Prototype 2 Figure 5-6	<ul style="list-style-type: none"> <li>-Addition of a list of concepts individually created.</li> <li>-Addition of software-based touch differentiation.</li> </ul>	<ul style="list-style-type: none"> <li>-Moving multiple elements at once.</li> <li>-Users had to explicitly indicate who did what by moving personal lenses onto the target elements.</li> </ul>
CMATE	<ul style="list-style-type: none"> <li>-Learner differentiation using COLLAID.</li> <li>-Displaying individual concept maps on the tabletop.</li> <li>-Addition of a list of linking words individually created.</li> <li>-Auto-organisation features.</li> <li>-Auto-rotation features.</li> <li>-Highlighting feature to allow students to mark the important links.</li> <li>-Infrastructure to divide the activity into phases.</li> <li>-Voting system to indicate when a phase is finished.</li> </ul>	<ul style="list-style-type: none"> <li>-A tool to help students to automatically add propositions they had in common.</li> <li>-A basic reflection tool to highlight possible issues in student's maps based on rules.</li> </ul>

The initial prototype (Figure 5-4) introduced basic features that allowed students to create concept maps and freely decide their own collaboration rules. These included basic editing options (add, delete or change concepts or links) and the use of virtual keyboards for editing text. The *black hole* elements were located at the corners of the tabletop. Students can drop unwanted elements of the concept map into the black holes. Each student is associated with one colour and each element added to the concept map was coloured according to the student who added it. In this version there was no user differentiation support. Students were asked to indicate who was adding a new element to the map through a user menu (menus at the corners of the tabletop in Figure 5-4). Users had to explicitly indicate who did what by pressing a button and taking turns to perform actions. This was a proof of concept of the kind of information that can be mirrored if user differentiation is supported.

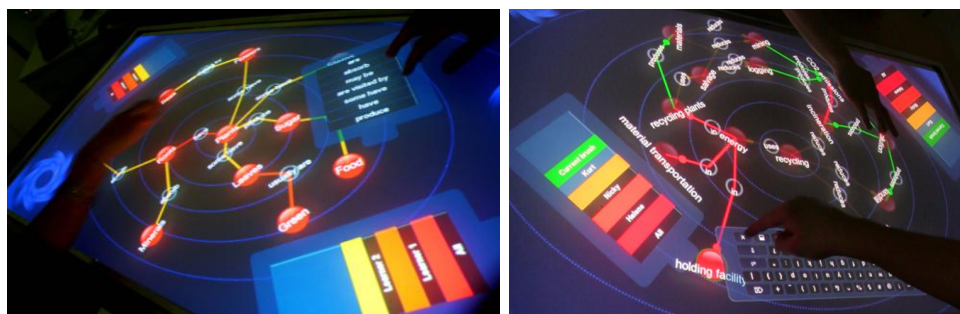


Figure 5-4 Initial prototype of CMATE with very basic features to edit a concept map.

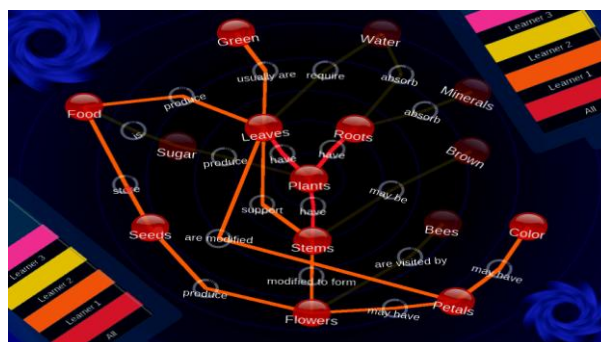


Figure 5-5 Initial prototype of CMATE: the application allows to highlight the sub-map by an specific student.

The interface produced in the second iteration is presented in Figure 5-6. The main features introduced in this prototype were the addition of a list of concepts obtained from an individual concept map created by each group member before working at the tabletop, and a software-based touch differentiation system. Users still had to explicitly indicate who did what, but this time by moving personal interactive areas or lenses onto the target elements. This way to differentiate touches produced usability issues that affected collaboration. This highlighted the need for an unobtrusive way to perform user differentiation. In this prototype users wore personal microphones to capture information of group member's speech. The final version of CMATE includes a series of features that allow students to decide how to collaborate and, at the same time, the system can automatically and unobtrusively track student's activity.



Figure 5-6 Second prototype of CMATE that includes a software-based user differentiation system.

### 5.3.2. System Final Features

CMATE can be linked to a well-known desktop-based learning tool called CMapTools server. First, before learners come to the tabletop, they can use this tool to build their individual concept maps in private (*v-Interconnecting with external devices*, refer to Section 5.2.1). Then, learners come together to the tabletop to discuss the commonalities and differences between their perspectives, and create a collaborative concept map. These individual concept maps are used by the tabletop application to extract the personal vocabulary of concepts and links, and make them available to the learners during the collaborative part of the activity (*iv, Integrating with services*). Thus, learners can use the concepts and links they previously included in their individual work, or create new ones and relate them with other participant's ideas to build a new mutually accepted artefact. Additionally, this information can be used by the application to offer hints on which parts of the personal concept maps are interesting to discuss.

The application allows a teacher to structure the concept mapping activity according to a script. For example, the concept mapping activity can be semi-structured in four stages: i) individual concept mapping (external to the tabletop); ii) brainstorming concepts at the tabletop; iii) adding propositions that the individual learners have in common, and iv) the linking phase in which users build relationships between concepts (*vi, Defining the degree of structure of the activity*). Regarding the user interactions with the tabletop, learners are initially provided with 3 tools: a list of concepts that includes the ones they used in the individual stage (or a list of suggested concepts if there was not an individual stage); an onscreen keyboard for editing phrases; and a resizable representation of their individual concept map. All these elements are initially minimised to avoid clutter (see Figure 5-7, top left). Learners can add concepts by simply selecting them from the list of concepts (Figure 5-7, top right) that is linked with the individual map that was built externally. They can add links by dragging a concept and dropping it on another target concept; and delete elements by dropping them on one of the pair of *black holes* situated on the corners of the tabletop.

The user interface is simple; in order to select any element at the tabletop to maximise it, edit a node (Figure 5-7, bottom left) or press buttons, the generalised interaction technique consists of a *touch and hold* gesture. This also gives some additional time for the system to resolve the authorship of the touch and thus, providing *real-time* feedback on each touch by representing each contact point with a different colour per user (Figure 5-7, top left). All elements at the tabletop are coloured according to the user who created such an object (Figure 5-7, bottom right).

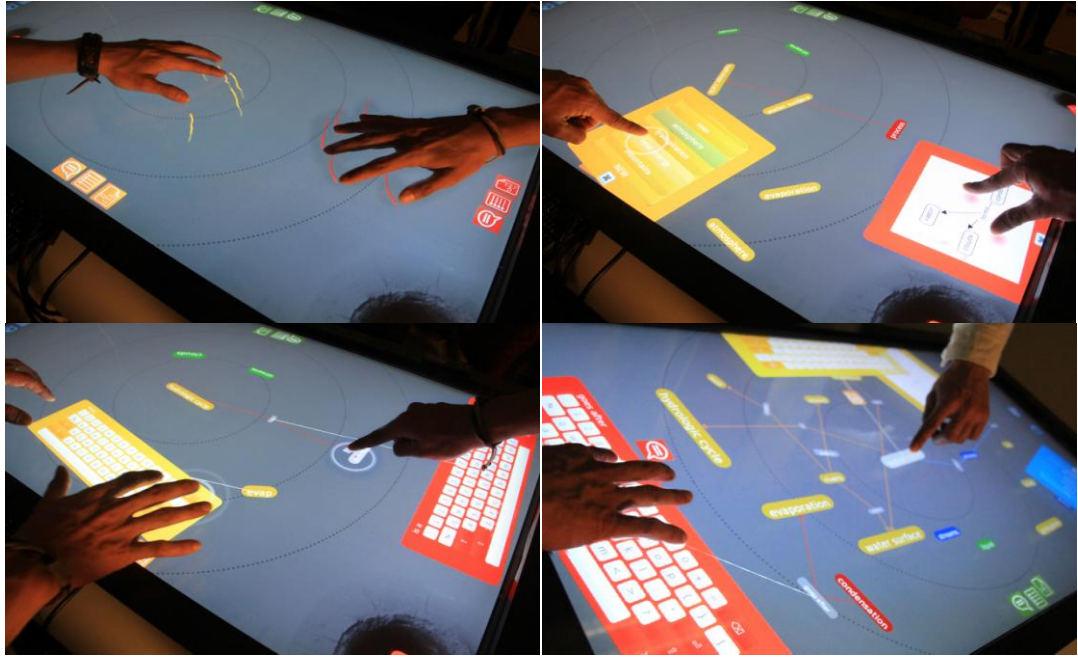


Figure 5-7 The concept mapping application. Top left: User identification; Top right: Accessing external sources; Bottom left: Editing node word; Bottom right: Building the artefact collaboratively.

### 5.3.3. Implementation Details

CMATE is platform independent, written in Python and OpenGL using PyMT<sup>1</sup>. We now describe the ways that the design was influenced by available design guidelines: those specifically for tabletop, by Scott et al. (2003) and Apted et al. (2009) as well as general heuristics by Nielsen (1994).

*Consideration for arrangement of users* (Scott et al., 2003). CMATE users are able to view and interact with the application at any position around the table. This poses a design problem in relation to the layout of the concept map. To address this, we introduced a new paradigm for the hierarchical structure layout. We chose a concentric hierarchy in which the most central concept is the best representative of the topic of the map. Then we provide circular lines as a map level reference, helping users arrange the concepts to reflect the levels of generality and identify similar concepts. Following the design guidelines given in (Apted et al., 2009; Scott et al., 2003) every element on the interface can easily be oriented as the user wishes by interacting with particular components.

*Support simultaneous user actions* (Scott et al., 2003). CMATE natively supports multi-touch interaction (given the adequate hardware). All students have similar opportunities of participation. All students can make contributions at any moment so they do not have to take turns.

*Support transitions between tabletop collaboration and external work* (Scott et al., 2003). As described in the scenario, CMATE allows teachers or designers to load the previously created individual concept maps. This can also provides the initial set of concepts and linking words to be re-used by students while building their group concept map. The design minimises the need for a keyboard, physical or emulated, to reduce clutter and make for simplicity.

*Support transitions between activities* (Scott et al., 2003). CMATE addresses this guideline by ensuring that users can move between all possible interface actions at any time. This includes creation of concepts and propositions, layer selection, drawing lines to link concepts, rearrangement of components and resizing/sliding menus.

<sup>1</sup> <http://pymt.eu/>



*Support transitions between individual and collaborative work* (Scott et al., 2003). A key challenge for tabletop interface design is to support the right balance between private activity and collaboration. This issue was a problem in (Do-Lenh et al., 2009), as users tended to work in parallel, without being aware about their peer's actions. In CMATE, students can agree to work simultaneously or they can decide to work separately. Students can decide between all focusing on explaining the subject matter using new concepts and linking words or to discuss the agreements or resolve conflicts between the ideas contained in the pre-loaded maps.

*Minimise human reach* (Apted et al., 2009; Nielsen, 1994). The design of CMATE ensures that the students can control the location of all concepts, linking words, menus and controls. All students are provided with the same controls and they are each within their reach.

*Use large selection points* (Apted et al., 2009): we provide large targets on the menus for the concepts and link terms. All elements of the CMATE interface also have large edge area targets for the rotate and resize gesture.

*Manage interface clutter* (Apted et al., 2009); we took the idea of the *black hole* from (Collins and Kay, 2008), enabling users to delete unwanted concepts or propositions by letting them fall into the metaphoric *black hole*.

### 5.3.4. Section Summary

**The section described our novel approach to support collaborative learning through concept mapping.** Taking account of problems observed in previous work we created the first design for CMATE. The iterative prototyping process helped us reduce the number of interface features. In this way we created a minimal but very usable concept mapping application from the student's perspective as a result of almost two years of iterative design. CMATE provides basic editing features and access to individual previously built maps, if available. Each study presented in later chapters, will be accompanied with details of the features of CMATE that were used for each specific learning activity. There are two main versions: *complete* and *minimal*. The *complete* version was used in lab settings (Chapters 6 and 7); and the *minimal* version was used in our studies in the classroom (Chapter 8).

## 5.4. COLLAID: an Enhanced Interactive Tabletop System

There is a growing body of research pointing at the importance of gathering contextual information when people collaborate at the tabletop<sup>1</sup>. This is needed to enhance or personalise user interface capabilities such as adapted content delivery (Ballendat et al., 2010), automatic orientation (Kruger et al., 2004), visualisations of collaboration around the tabletop (Bachour et al., 2010; Tang et al., 2010), application of data mining techniques to find salient patterns of interaction or building a user model to adapt the support that the tabletop system can offer (Martín and Haya, 2010).

As stated in Section 5.2, currently, there are no guidelines to inform the design process for tabletop software designers, so as to capture the right information to create such user models or for further data mining to enhance these models. In addition, the hardware currently available often fails to distinguish which activities were associated with each person at the table (see Section 2.3.2).

In this section we show how the key design principles outlined in the Section 5.2 were followed to design and implement our COLLAID (Collaborative Learning Aid) environment. We map each of COLLAID's features to the guidelines. And finally, we validate the usefulness of COLLAID in a case study that makes use of its elements to capture information that can be exploited for various purposes such as visualising collaboration or feeding educational data mining techniques.

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<sup>1</sup> Parts of this section have been published in the proceedings of ITS2011 (Martinez-Maldonado et al., 2011b) and at the Work-In Progress track of CHI2012 (Ackad et al., 2012).

### 5.4.1. The Multimodal Environment

#### *Physical generic setting.*

The tabletop used during the design and implementation of COLLAID had a 46-inch LCD touch screen with a display resolution of 1920x1080 pixels. The tabletop hardware can detect multiple touches at a time, but – like most current touch hardware – it cannot recognise which user is providing an input. To give support to the model for capturing group member’s interactions (design guideline: *i-Distinguishing users*, refer to Section 5.2.1) we designed a system based on a depth sensor<sup>1</sup> located above the tabletop to track the position of each user’s body and arms (Figure 5-8). We match the depth images generated by the sensor (Figure 5-8, top left) with each touch performed on the interactive tabletop identifying the finger that is touching the table in that exact position, at that precise moment. Then, using a greedy search algorithm (weighted to make it follow the shape of arms, Figure 5-8), we detect the arm span of that learner, so recognising the owner of that touch according to their position around the table.

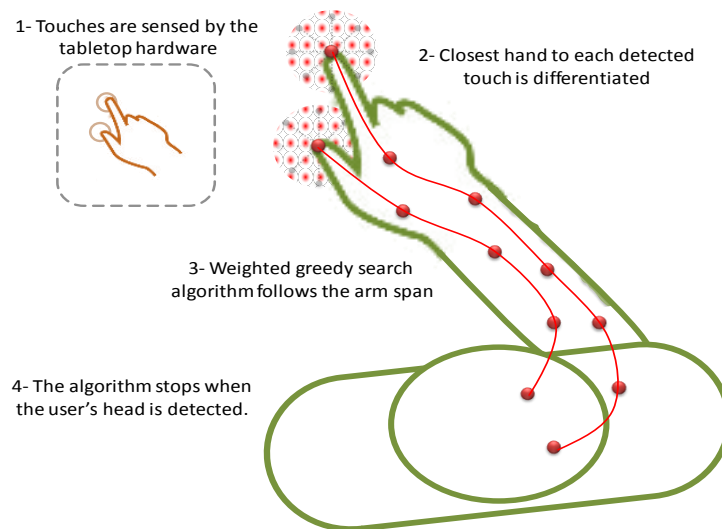


Figure 5-8 Weighted Greedy Search Algorithm to differentiate users using COLLAID.

However, as mentioned earlier, most of the collaborative interactions among *collocated* users do not occur between the computer and people, but between the users themselves (*ii-Capturing verbal communication*). In order to capture this important dimension of the collaborative process, we capture the speech and verbal participation through an array of microphones<sup>2</sup> situated above or at one of the edges of the tabletop (Figure 5-9, right). We use a radial 7-channel USB microphone array that can distinguish sounds based on the spatial location of the source, in our case, the learners who are collocated around the tabletop. The array recognises when a learner is speaking. Then, the application links the source of the sound with the learner’s position to finally record the audio information to audio files and the shared database.

Through this set of hardware, we unobtrusively obtained a range of sources of student’s data: verbal interactions between learners (without attaching microphones to people) and tabletop data logs with the authorship of each touch (without attaching any gadget to people’s hands or having additional furniture). Figure 5-9 shows the generic disposition of the sensors of the system. This setting can potentially be used in a number of environments like classrooms, public spaces or controlled research settings. However, an additional function may be useful in some cases where users need to be able to identify themselves (*login*). This would make it suitable for *walk-up-and-work* settings in which the tabletop is deployed in a shared space. We discuss this in detail in Appendix Section A.3.

<sup>1</sup> <http://www.xbox.com/kinect>

<sup>2</sup> <http://www.dev-audio.com>



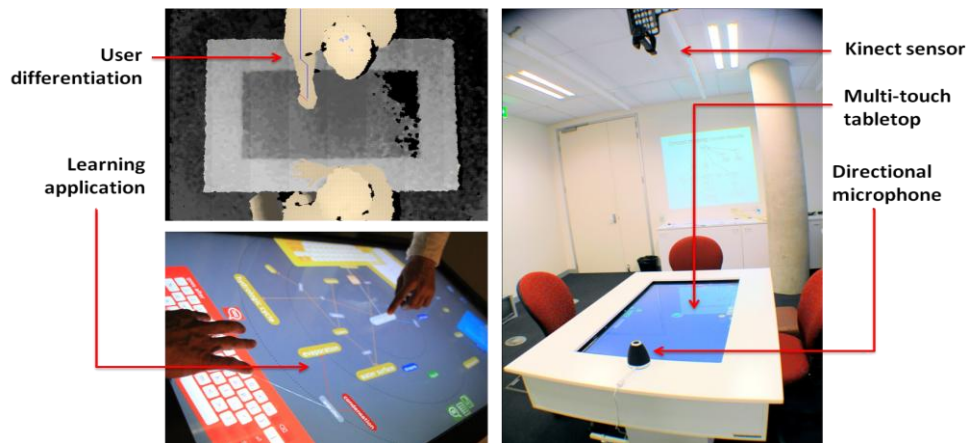


Figure 5-9 Digital learning environment and capturing system.

### Software architecture.

The software architecture of this system is distributed across a number of applications that can get information from the corresponding sensors, record it into a central data server or use it to show indicators of collaboration to the users. The advantages of using a common repository of information, instead of log files, is that the sensing applications can save information at the same time that a number of services (such as *real-time* monitoring systems or machine learning techniques) can make use of these data (Mostow, 2004) (*x-Recording to a database*, refer to Section 5.2.2). The software architecture consists of 4 key parts, as illustrated in Figure 5-10. The first block corresponds to the set of applications that are connected to the sensors with the purpose of capturing information about the activity of the students (left green box). These include the applications for capturing and mapping the position of users with the tabletop, the application for recording the verbal utterances and process the speech content, and the regular system for capturing the touches at the tabletop. This part of the system is generic and can be used with any tabletop application.

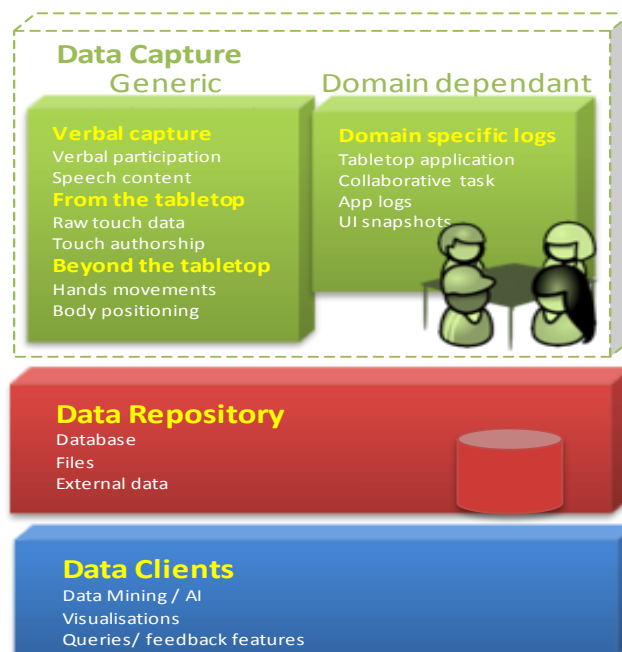


Figure 5-10 COLLAID software architecture.

The second block (right green box) corresponds to the tabletop application that gives support for learning, training or any other collaborative activity (e.g. CMATE). This part of the system is heavily dependent on the domain of the activity and the learning goals of the group of learners. The

application logs should contain the contextual information about what the learners intended to do at the tabletop, rather than just the raw *touch- down and up* events. Therefore, the meaning of the logs depends on the range of the possible actions permitted by the design of the tabletop application. This information can be formatted as a long ordered sequence of user actions or as a set of *snapshots* of the state of the tabletop at regular intervals. The third part is the data repository (red box) that can reside in a central file system or a database server in which all the sensing applications can synchronously record time-stamped event data, and the client services get information out (*iii, Integrating user and contextual data*).

Finally, the data can easily be accessed by different services to feed data mining engines, visualise the collaborative data, perform queries or provide adapted support to the collaborative activity (*iv, Integrating with services*). In this section, we explore the accuracy of the system to differentiate student's input and the feasibility of the approach to support data mining analysis. The next chapter explores the generation of visual representations of students data (Chapter 6).

#### *Dataset description.*

Each touch action on the tabletop is recorded at two levels: the *raw data*, that include each touch and motion of a finger across the tabletop; and *application logs*, that include meaningful actions like moving, creating, deleting or pressing on objects at the tabletop. The latter is the level of logging our approach is focused on (*ix, Defining the logging semantic*). The application-level logging includes the information about the time the action started and finished, the initial and final position/rotation/size, if the action involves the manipulation of an object, the status about the status of that object and the author of such actions. The system records the information of the status of each element on the tabletop every second, the position of learners around the tabletop, and verbal utterances (*viii, Capturing the data in multiple formats*).

## 5.4.2. Case Study and Validation of the System

We conducted both a quantitative analysis and a qualitative case study evaluation to demonstrate how the COLLAID environment can effectively enable the collection of collaboration data and be used for running data mining algorithms to extract frequent patterns.

#### *Quantitative analysis: touch differentiation accuracy<sup>1</sup>.*

The first validation of the system presented in this section is a basic accuracy testing for both the touch and speech differentiation features of COLLAID. We validated the touch differentiation system. Here, we report a study conducted using a testing user interface shown in Figure 5-11. This interface presents to a number of users (from 2 to 6 users) a set of patterns consisting of a number of coloured points that the users are requested to touch. These coloured touch points are randomly shown in sets of 1, 2, 3, 4, 5, 6, 7, 8, 9 and 10 dots per user. Each user is associated with a specific colour so they are asked to only touch the points of their colour. We validate whether COLLAID correctly distinguishes the user who touches each point. This evaluation was divided into two phases; first, with the participants seated and the second, with the participants standing (the latter as shown in Figure 5-11). There were 2 different patterns per number of dots and each test was repeated twice.

We evaluate 5 group sizes: 2, 3, 4, 5 and 6 users. This means that each group size included 40 different tests (2 sets for the 10 random patterns -repeated twice- for two seating conditions). When a point on the tabletop was touched, the colour of the point changed from its original colour to grey to distinguish that the point as having been pressed. In this way it is possible to measure the number of errors that our system makes when resolving a touch point under challenging conditions for the over-head vision- based tracking system (e.g. users being too close to each other or crossing their arms as shown in Figure 5-11).

<sup>1</sup> This evaluation was conducted in collaboration with Christopher Ackad and Andrew Clayphan. (Clayphan et al., 2013b).



Figure 5-11 Evaluation of user differentiation features of the COLLAID environment.

Table 5-3 outlines the levels of accuracy and the proportion of false positives detected by the system. For brevity, only the cases with 1, 5 and 10 touches per user are shown in the table. Our vision-based touch identification provides very high rates of accuracy for up to 5 users working simultaneously at the tabletop. The number of touch points in each test corresponds to the load of activity that the tabletop application is expecting to have. For example, some tabletop applications that show big objects or do not require the introduction of text would be associated with low levels of input load. Other applications may require users to introduce many commands, such as typing text, interacting with many small objects or for some video games.

Table 5-3 Accuracy of the touch differentiation system according to the number of users.

Users	Touch per user	Total touches	Accuracy	False positives
2	1	16	94%	1
	5	80	98%	2
	10	160	98%	4
3	1	24	92%	2
	5	120	92%	10
	10	240	93%	16
4	1	32	94%	2
	5	160	91%	15
	10	320	89%	34
5	1	40	100%	0
	5	200	88%	25
	10	400	88%	50
6	1	48	77%	11
	5	240	85%	35
	10	480	83%	83

**The system offers accuracy levels around and above 90% for all levels of input load.** The accuracy of the system starts to decay for high input loads when 5 or 6 users interact simultaneously around the interactive tabletop. In this thesis, all studies conducted in the lab (Chapters 6 and 7) involved the participation of 3 or up to 4 learners. Therefore, the system provides very high accuracy to differentiate student's input. For our studies in the classroom (Chapter 8), each tabletop had room for up to 6 students; however, most of the groups had 5 students or less. Additionally, the analysis included the evaluation of conditions that were predicted to be pathological for our kind of vision system, such as touches, by different students, occurring very close to each other or arms crossing. In this way, we were able to design CMATE around those conditions so they were less likely to occur. The full details of this evaluation are presented in Appendix Section A.2.

*Quantitative analysis: speech differentiation accuracy.*

For the case of the speaker differentiation system, we performed a formative study on a sample of 30 minutes of recorded user interaction. The objective was two fold: 1) validate that the utterances as detected by the microphone array were real and not other kinds of sound (e.g. users

making noise, changing position, coughing, etc); and 2) investigate if it is possible to automatically detect if an utterance is triggering new conversation or it is responding to other user's speech.

The sample data was manually tagged by analysing the video of users using CMATE. Each period of speech of each user as detected by the microphone was tagged as one of three possible values: *starting utterance* corresponds to cases that are not responses to other user's comments and introduce a new idea; these utterances usually do not have any other utterance immediately before; a *responding utterance* is registered when a utterance immediately follows a previous utterance from another learner (or happens simultaneously); and *no utterance* tags were used for those detected sounds that did not correspond to actual speech. In parallel, we programmed the same simple rules to automatically categorise all the utterances in our dataset according to their appearance in the timeline.

Table 5-4 shows the results of comparing the observed utterances with the automatically detected speaking moments. The most important result for this study was the very low quantity of false positive utterances detected (less than the 5% of all utterances detected). This rate is very acceptable for the kind of studies conducted in this thesis. This means that the microphone correctly detects 95% of the utterances produced by students and the other 5% corresponds to noise produced by users. We additionally compared the rule-based tagging with the human tagging to differentiate if a utterance was either triggering new talk responding. We found 76% agreement in identifying learner's verbal responses with the details shown in Table 5-4. This second exploration is not relevant for the kind of validation presented in this section but it is very important for discovering trends of collaborative learning, as will be investigated in Chapter 7.

Table 5-4 Accuracy of the speaker differentiation system.

Utterance type	Correctly identified by a rule-based model	Observed identification	Errors
Starting	92	228	9
Response	296	313	18

#### *Qualitative case study: Discovering patterns.*

The second technique that we explored to validate COLLAID was the application of a data mining procedure to discover patterns of student's interaction that are hard to find by simple inspection of the logs. We conducted this analysis with 9 participants organised in groups of 3. They were students predominantly enrolled in computer science courses and were aged between 25 and 30. Group members were familiar with one another. They were asked to build an artefact collaboratively at the tabletop using CMATE. The main goal of this analysis is to validate that the data captured by COLLAID can be analysed through data mining techniques to find patterns of interaction.

The data mining task we set out to solve was to discover the frequent sequences of interactions with the user interface performed by each learner at the tabletop. Two key attributes of this tabletop dataset are: the authorship and the sequential order of each action. One technique that proved effective in analysing the timing and order of the events was sequential pattern mining. The algorithm used in this case is a simplified version of the sequential mining approach presented in the *Study Newcastle* (see Section 4.4). The sequences extracted in this analysis are exclusively focused on the *consecutively* ordered sub-set of events that can potentially form a pattern. We do not consider the non-consecutive actions because frequent patterns of a pair of actions might not be meaningful if many other events or large gaps of inactivity occur between such actions.

Table 5-5 Basic actions considered for the data mining sequential mining.

AC-Add concept	O-Reorient element	MT-Move tool
AL-Add Link	D-Delete element	ML-Move link
M-Maximise menu	EC-Edit concept	MC-Move concept
m-minimise menu	EL-Edit link	

Table 5-5 shows the simplified set of actions that learners can perform on the tabletop (*ix-Defining the logging semantics, x-Defining the format of the data according to the data mining technique*). As mentioned in Section 5.2, the raw logged touches do not indicate the intention of the users. In our approach, raw student actions were pre-processed and a long sequence of actions *per learner* was generated to obtain a total of 12 long sequences (one for each participant). Then, we split these long sequences when a considerable gap of inactivity was found (an arbitrary threshold of 15 seconds of inactivity was chosen). For example, we got a sequence of actions {M-AC-AC-MC-MC-AL-m} performed by “Alfred”. He started the activity by opening the list of concepts he included in his personal artefact (M), then added a couple of concepts (AC), rearranged these elements (MC) and created a link between them (AL). In this case, if “Alfred” did not do any other action for more than 15 seconds then his first generated sequence of events would be similar to the sequence presented above. The goal is to find how many times “Alfred”, or other learners, repeated this same sequence of events or at least part of it. In other words, the aim is to look for frequent ordered patterns within the action sequences.

With the purpose of detecting both the frequency and redundancy of the patterns of interaction, we implemented an extraction algorithm of n-grams. An n-gram is a sub-sequence of n elements from a given sequence. Only sequences of at least 3 actions were considered (n=3). We fixed the minimum support threshold at 10 times to consider a pattern as frequent. The output of the algorithm is a list of frequent sequential patterns that meet the minimum given support. Based on the full sequences generated in this way, our algorithm seeks consecutive and also repeated patterns within the dataset of sequences. For example, following the initial example, if we identify from our dataset that “Alfred”, along with other learners, performed the sequential sub-set of actions {AC-AC-MC-MC-AL} more than 10 times, then our algorithm will list this sequential pattern as frequent. The resulting output was a list of frequent patterns. The result had 69 frequent patterns, of length varying from 3 to 17 actions.

We obtained interesting results about the way learners interacted with the user interface. Table 5-6 shows the top-most frequent sequences found in the dataset and their distribution across 3 groups. These results show that many of the actions are dedicated to reorganising the content in the concept map (move links and concepts). However, it is hard to tell the impact of these actions or the factors that motivated students to move elements of the map instead of focusing on creating propositions. The small study does not allow us to investigate possible differences among groups.

Table 5-6 Top frequent discovered patterns and its frequency per group. Columns G1, G2 and G3 specify the partial frequency for groups 1, 2 and 3.

Sequence	Action	F	G1	G2	G3
ML-MC-ML-MC	Move content elements	224	77	98	60
ML-ML-ML	Move content elements	146	64	46	42
ML-MC-ML	Move content elements	106	48	31	32
MC-ML-ML-ML	Move content elements	78	38	22	19
AL-ML-ML	Add link	57	11	29	17
MC-AL-ML	Add link	37	10	16	11
MT-AC-MC	Move tool and add concept	27	6	12	9
MC-EL-ML	Edit linking word	25	13	1	9
MC-MC-AL-MC	Move content and add link	24	4	8	12

More groups need to be analysed to find possible trends in terms of the level of collaboration. To be useful, the sequences need to provide more contextual data so the information offered by the patterns can be triangulated with other kinds of evidence. For example, it would be interesting to include contextual information about the speech, consecutive actions by different learners, the kind of concepts or links that are being added, their relevance, if they have been considered by students in previous tasks or if they form part of newly created knowledge. Deeper data mining analyses are needed. This is the motivation for the larger studies presented in the following chapters.

### 5.4.3. Section Summary

In this section we described the construction of COLLAID, an environment that captures and records, in a *non-intrusive way*, student's collaborative interactions. COLLAID allows learners to naturally interact with the system and between themselves, instead of asking them to adapt their behaviour to the hardware or software features. We also described a case study that illustrated the feasibility of using COLLAID to analyse student's data. We showed that the pattern mining technique described in Section 4.4 is also applicable to this tabletop dataset. We demonstrated that the data can be mined and that it should be integrated with different sources of information.

## 5.5. Chapter summary

Using the guidelines described in Section 5.2, we implemented a tabletop learning environment that can capture, in a *non-intrusive way*, the collaborative interactions of people as they build a joint solution. Our sensing environment, COLLAID, can be attached to pre-existing tabletop hardware to extend their affordances by distinguishing user's touches and verbal participation.

We also presented CMATE, our multiuser tabletop concept mapping application that is used in several studies in this thesis. The design of CMATE involved an iterative prototyping process in which usability tests and analyses of collaboration were conducted in order to refine the system features. The objective was to set a number of features and user functionalities that allowed students to decide how to collaborate. Finally, we mapped each of the design guidelines for capturing and formatting tabletop data with our own implementations. Table 5-7 presents our systems features described in terms of each of the guidelines.

Table 5-7 Mapping the system features with the designing guidelines.

Design Guideline	System Feature
<i>i-</i> Distinguishing users	User touch identification using a depth camera (COLLAID)
<i>ii-</i> Capturing verbal communication.	Hands-free speech differentiation using a microphone array (COLLAID)
<i>iii-</i> Integrating user and contextual data.	Desktop-based external work (CMATE) Position of user around the tabletop (COLLAID)
<i>iv-</i> Integrating with services	Input services: CmapTools Server files (CMATE) Output services: visualisation dashboard, sequence pattern mining.
<i>v-</i> Interconnecting with external devices.	Multi-touch dashboard, personal computers, (see Chapter 8)
<i>vi-</i> Capturing speech/video information	Performed in studies but it was not automatically implemented.
<i>vii-</i> Defining the degree of structure of the activity.	Semi-structured activity in three stages: i) individual concept map, ii) brainstorming concepts at the tabletop and iii) linking phase.
<i>viii-</i> Capturing the data in multiple formats	Sequential log for data mining Timely snapshots of the tabletop layout for the visualisations
<i>ix-</i> Defining the logging semantic	Basic semantic level (application logs CMATE)
<i>x-</i> Recording to a database	Activity data from different sources recorded in a central repository.

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## Chapter 6: Visualisation of Group Indicators and Teacher's Dashboard

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*"Because the teacher can see clearly, light is shed on others"*  
-The Tao of Teaching, by Greta Nagel

**Summary:** This chapter presents an approach to produce group indicators, and their visual representations, of student's collaborative interactions at an interactive tabletop. We explore the effectiveness of the visualisations in enhancing teacher's awareness. In particular, we produce summaries of group's activity that are effective enough to allow teachers decide how to divide their attention in the class. First, we report on the effectiveness of group indicators to describe different cases of collaborative learning. Secondly, we describe the design and evaluation of visual representations of some of these indicators. They depict various aspects of group work, including: individual contributions, levels of collaboration, equity of verbal communication, symmetry of touch activity, student's interactions, and evolution of the group artefacts. Third, we present the deployment of these visualisations in a teacher's dashboard. We use simple data plotting, formulas and a classification model to produce these visualisations. We analysed the nature of the information as perceived by real teachers, who only inspected these visualisations, in order to take decisions about which groups may need closer attention.<sup>1</sup>

### 6.1. Introduction

One of the main challenges for teachers in *orchestrating* multiple groups working face-to-face is that they need to determine the right moment to intervene and how to divide their attention effectively among the groups (Dillenbourg et al., 2011). Often teachers only see the final product that does not reveal the processes students followed (Race, 2001). This means teachers cannot act effectively as facilitators for the learning of group skills. This is a problem because teachers may find it hard to evaluate the collaborative processes and certain aspects of group work such as the symmetry of participation (Dillenbourg, 1998), high quality partial solutions or student's individual contributions. This problem can dissuade teachers from using group work. Yet, there is acknowledged value in collaborative knowledge creation (Paavola and Hakkarainen, 2005).

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<sup>1</sup> Parts of this chapter have been published in international conference proceedings of CSCL2011 (Martinez-Maldonado et al., 2011d), ITS2012 – Intelligent Tutoring Systems (Martinez-Maldonado et al., 2012f), ICLS2012 (Martinez-Maldonado et al., 2012g) and at the international workshop EIST held in CHI2012 (Martinez-Maldonado et al., 2012b).

There has been considerable work exploring the importance of group visualisations to externalise the activity of groups and, in many cases, to reveal relationships between observable patterns and the quality of the group work. Our work is especially inspired by previous research conducted by Erickson et al. (1999), who created the *social proxy*, a visualisation of chat sessions of a group. The visualisation of plain quantitative information of participation resulted in improved collaboration and better support for people to learn how to collaborate. In the same way, *sociograms* have been extensively used in the CSCL field to visualise learner interactions and to represent the lines of communication within social networks (Sundararajan, 2010). We additionally build on work conducted by Kay et al. (2006), who created a set of visualisations to identify anomalies in team work by mirroring aspects such as participation, interaction and leadership.

This chapter presents **the design and evaluation of a number of visual representations of indicators of group's collaboration, performance and evolution of their task**. Having described the implementation of our technology infrastructure to capture student's interactions in the previous chapter, this chapter evaluates the impact of distilling such data and presenting it to the teacher to enhance their awareness and decision making (this is mainly explored in Section 6.4).

Figure 6-1 shows the goals, contributions and validation methods of this chapter. The visual representations of student's interactions are validated through two main studies. The first study consists of the design of a set of visualisations that can be automatically generated from our enhanced tabletop environment. This first set of visualisations is then evaluated by teachers who are requested to respond to key questions about student's collaborative work based on the analysis of the visual information provided.

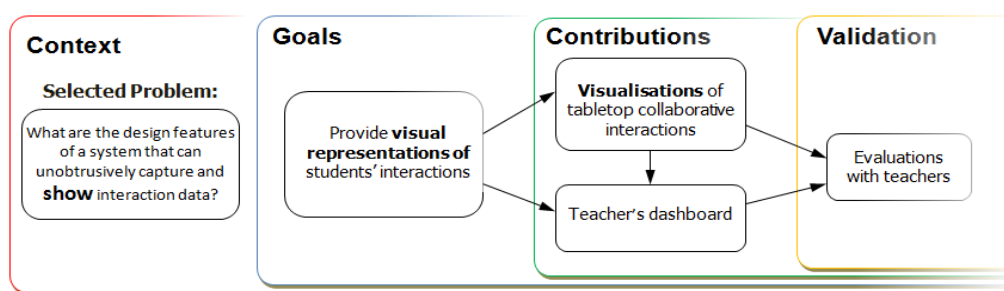


Figure 6-1 Context, goals, contributions and validation of Chapter 6.

The second study presents the design and evaluation of a teacher's dashboard that shows information of up to three small groups working simultaneously. This information is presented at two levels: minimal information that can be shown during a classroom session; and more detailed visual data that shows the progress of student's action that is more suitable for post-hoc analysis. For these two studies, real teachers participated in the validation of the proposed tools. The teachers were not involved in any part of the design of the solutions. The aim of the validation of the visualisations presented in this chapter is to produce the building blocks to deploy an integrated solution in the classroom (which will be presented in Chapter 8).

Figure 6-2 shows the components of our conceptual framework (TSCL-CF) that are in this chapter. Grounding on the elements of the Data Capture Foundation (DCF) presented in the previous chapter, we present an approach to automatically generate visual representations of Group Indicators (GI) by analysing student's tabletop data. Some visualisations just mirror the logged actions captured by the Sensing System. Other visualisations show aggregated quantitative measures of group participation obtained through basic descriptive statistics. We present one visualisation that reflects information processed through a model learnt by a data mining technique. The goal is to validate a number of visualisations and the teacher's dashboard that would be part the Data Presentation Foundation (DPF) to be deployed at an authentic learning scenario. The visualisations may also be used as open learner model to be shown to students. But our work deals with them as awareness tools to drive teacher's source of attention during the activity or for post-hoc analysis of what happened with some groups in the classroom.



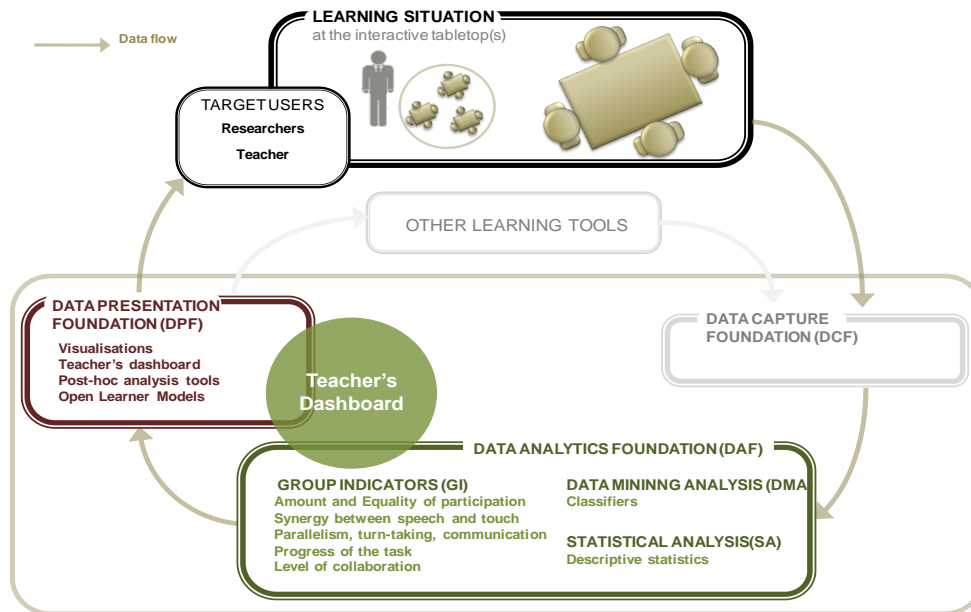


Figure 6-2 Detailed of the TSCL-CF focused on the visualisations and teacher's dashboard.

This chapter is structured as follows. Section 6.2 presents findings from a small-scale study analysing the effectiveness of produced group indicators to describe different cases of group strategies. Section 6.3 presents the design and evaluation of a first set of visual representations of group's indicators. Finally, Section 6.4 presents the deployment of a second set of visualisations in a teacher's dashboard. The goal of this dashboard is two-fold: presenting sufficient information to make the collaboration process interpretable without overwhelming the teacher in the classroom; and showing detailed traces of a group's activity for post-hoc analysis.

## 6.2. Group Indicators and Traces of Collaboration

The study described in this section investigates indicators of collaborative learning captured by our tabletop environment (COLLAID and CMATE) that can provide teachers with information about the ongoing collaborative work<sup>1</sup>. The work reported in this section describes findings of a case-study that aimed to apply our tabletop environment as a shared space for group collaboration where students can decide how to integrate their *individual ideas*. The question this study addresses is: *what indicators can be automatically produced, from a tabletop learning environment, that complement the empirical observations made by a teacher?* Figure 6-3 shows the main parts of the learning environment and the group indicators that are explored in this study.

### 6.2.1. The Learning Environment

In this study COLLAID was used to recognise touch input and speech participation from different users. Fifteen university students participated in the case study. All participants were native English-speakers, predominantly enrolled in engineering courses and were aged between 20 and 26. Participants were assigned to groups of three and knew each other. The design of the experiment had two phases: an individual one at a personal desktop followed by a collaborative one at the tabletop. The duration of each session included (1) a 10 minute reading phase, (2) up to 30 minutes for building the individual maps, (3) up to 40 minutes for the collaborative phase at the tabletop and (4) a reflection phase where the interface shows the propositions that students included in their individual maps but not in the group map. First, participants were introduced to the concept

<sup>1</sup> Parts of this section have been published in the proceedings of ICLS2012 (Martinez-Maldonado et al., 2012g) and at the workshop EIST held in CHI2012 (Martinez-Maldonado et al., 2012b).

mapping technique. They were instructed to generate a small training concept map about a familiar topic. Then, all participants read the same text about the learning domain (human nutrition). They individually generated concept maps using CmapTools on computers answering a focus question on human nutrition. They received an initial list of suggested concepts extracted from the instructional text to build their concept map. They were free to add their own concepts, hierarchical arrangements, and linking words. After completing their individual concept maps, the group was asked to collaboratively build a shared concept map using the tabletop.

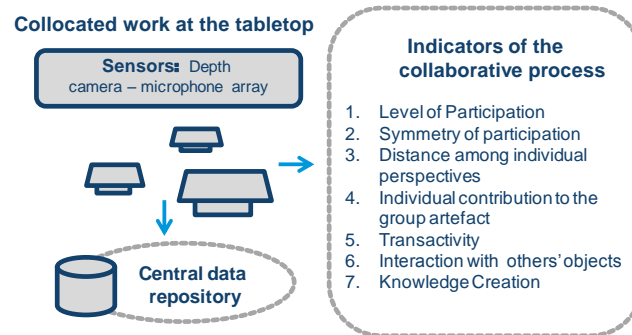


Figure 6-3 Disposition of the parts of the learning environment and the group indicators explored in this study.

The second phase consisted of building a collaborative concept map at the tabletop, using the final version of CMATE (see Section 0 for details). This second phase was scripted in four stages (see Figure 6-4):

1. *Selecting concepts*; participants were asked to add the concepts that they considered are the most general from their individual concept maps. New concepts could also be added in later stages.
2. *Adding propositions that the individual learners have in common*; the tabletop loads the individual final maps and validated which propositions were similar and asked learners whether they wanted to add these.
3. *Linking phase*, in which users built relationships between concepts (propositions); this was the common concept mapping process.
4. *Reflection on the resulting map*; the application highlighted potential errors (e.g. duplicate concepts) and suggested propositions that were included in some of the individual maps but were missing in the group map.

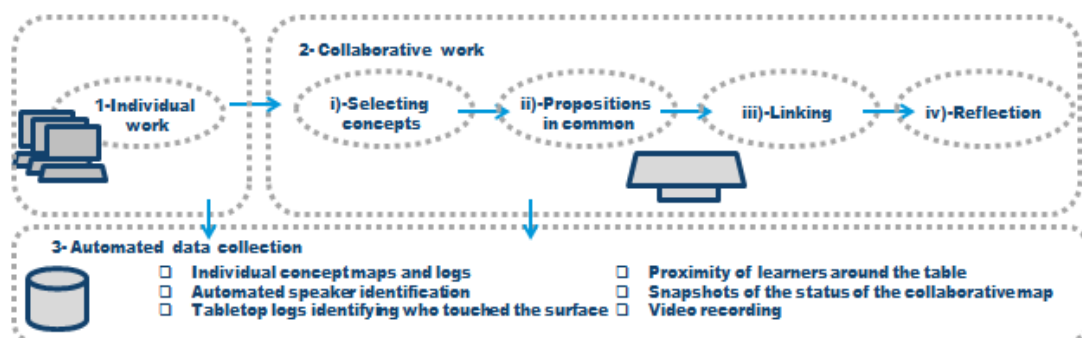


Figure 6-4 Approach: 1) individual work using personal computers, 2) group activity at the tabletop and 3) the information readily available from the capture performed by our environment.

During the two phases, data was automatically collected from the concept mapping applications and from video and audio traces (see Figure 6-4). The disposition of students around the tabletop for the 5 sessions is shown in Figure 6-5. Through this study, learners had access to their list of concepts, including the ones they used in the individual stage. They could choose to add concepts

they consider important to share with others. However, they could also decide to not to collaborate, to build three separate concept maps or leave one student to do all the work.

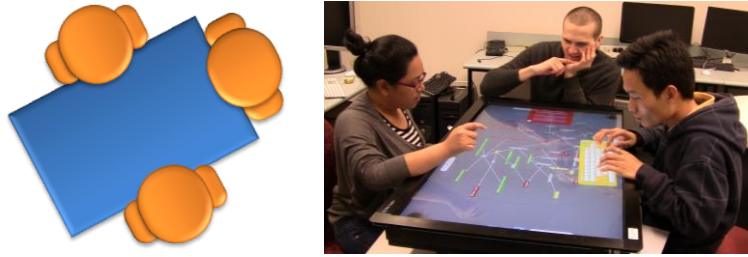


Figure 6-5 Left: Position of learners around the tabletop in this study. Right: Collaborative concept mapping application being used by three learners.

### 6.2.2. Dataset Description

Triads spent 35 minutes on average on the collaborative tabletop concept map construction (excluding the reflection phase). Between 450 and 1102 meaningful *physical actions* on the tabletop were recorded per group. Speech data was captured distinguishing when each group member was speaking. Individual participants spoke between 2 and 15.6 minutes. Qualitative observations were conducted to assess if most of group's speech was on-task (above the 89% of the conversation in each group). Each utterance in a sample of each session (more than the half of each session) was coded according to a modified coding scheme for Collaborative Decision Making (Kennedy-Clark et al., 2011). Off-task speech included all the utterances about anything other than the *subject material*, *articulation of the group* or the *interaction with the application*.

### 6.2.3. Group Indicators and Data Analysis

This study focuses on analysing a set of *indicators* that measure the degree of participation, knowledge distance, and interaction within the groups. These indicators were chosen based on previous investigations that have used them to aid empirical and quantitative studies of group learning (Anaya and Boticario, 2011; Bachour et al., 2010; Dillenbourg, 1998; Molinari et al., 2008; Paavola and Hakkarainen, 2005; Taricani and Clariana, 2006).

1. *Level of Participation* – verbal and physical. This dimension of the collaborative activity is a very basic indicator of the extent to which learners participate and how they do it compared with other learners within the same group or among other groups. The tabletop environment automatically captures two dimensions of participation: The physical participation includes all the touches that are performed on the interactive surface to trigger any meaningful action in the application (e.g. create concept, add link, and edit linking words). This is the dimension of participation that is commonly investigated in e-learning settings (Anaya and Boticario, 2011). However, in a collocated environment what is said possibly has more impact on the group decisions (Bachour et al., 2010). Therefore, we captured when a learner was talking.
2. *Symmetry of participation* – verbal and physical. It has been found that groups in which students participate asymmetrically are frequently related to cases of free-riding or disengagement from the activity (Dillenbourg, 1998). Groups that behave collaboratively tend to allow the contribution of all group members. The Gini coefficient was used as an indicator of symmetry of participation in both dimensions: physical and verbal. As described in Section 4.2. For this coefficient, a value of zero means total equality and a value of one indicates maximal asymmetry. However, we learnt from the study described in Section 4.3 that coefficients close to .5 also identify group situations that are asymmetric.
3. *Distance among individual perspectives*. This study aims to measure the extent to which the individual perspectives about the topic are similar to each other. This study uses concept maps as indicators of understanding. Taricani & Clariana (2006) developed a technique for scoring

open-ended concept maps by comparing them with a master map. Inspired by this approach, in this study we applied a similar automatic technique but with the purpose of comparing student's concept maps.

4. *Individual contribution to the group artefact.* Applying this technique (Taricani and Clariana, 2006) we also measure the distance between the individual concept maps and the group concept map. However, unlike Taricani & Clariana (2006), we can measure this distance all through the collaborative process to observe how this individual contribution varies across time. In this case the distance is another indicator of contribution.

5. *Transactivity.* In the context of collaborative concept mapping, transactivity has been described as the extent to which a group member refers to or builds upon their peer's contribution while adding their own ideas to the group map (Molinari et al., 2008). We measure this in terms of the number of links that each learner creates using concepts that other learners added to the group map.

6. *Interaction with other's objects.* Another way to measure interactions among group members is to see how often they interact with the same objects (e.g. one learner adds a concept, then a second learner moves and edits the concept word, then a third learner creates a link using this concept). This indicates that the three learners are at least aware of the presence of the concept in the context of the activity. In e-learning contexts this indicator has been used to measure degree of collaboration of the learners (Anaya and Boticario, 2011).

7. *Knowledge Creation.* Following the metaphor of knowledge creation of Paavola & Hakkarainen (2005) we measure the *created knowledge* in the context of concept mapping by distinguishing links that were used in the shared map but not in any individual map. This indicator does not describe the correctness of these links. Nor does it compare the map with a master map. By contrast, it highlights the propositions that were constructed as a result of the collaborative knowledge building process.

## 6.2.4. Results

This study focuses on four of the five groups that had distinctive collaborative behaviours. Students in Group 1 worked totally independently; Group 2 was a collaborative group; in the third Group there was a dominant student who did not allow other students to contribute; and in Group 4 there was an under-participating student (free-rider). Table 6-1 shows the group indicators produced for each of these groups. The row that corresponds to *Level of Participation (group)* shows the number of touches or speaking time by the three students of each group compared with the mean of all four groups (average number of touches on the tabletop per group=312, SD=241; average talking time per group=7.2 minutes, SD=3.5). For example, the group in which participants worked independently (Group 1) had 817 touches and 12 minutes of talk. The number of touches and the amount of talk were normalised to one of three possible values: "Low" if the number of touches was lower than the mean - 1 SD, "Med" for the interval of 1 SD around the mean, and "High" if mean + 1 SD. In addition, each member's participation was tagged as "Low", "Med", or "High" according to the mean number of touches and verbal participation among the members of the same group.

Row 2 shows the symmetry for the physical (touches) and verbal participation among members, using the average of the Gini coefficient sampled every two minutes of activity of concept mapping at the tabletop. For example, the minimum Gini coefficient corresponds to the verbal participation of group 2 (0.16) indicating that the speaking time of group members was balanced. By contrast, a Gini coefficient of 0.5 for verbal participation of group 4 reflects the lack of participation of one of the group members compared with the other two.

Row 3 has the distance between the individual maps of the members of the same group. P1, P2, and P3 correspond to Participants 1, 2 and 3. A percentage of 5% indicates that both individual concept maps shared 5% of the propositions (links); an indicator of how close their preconceptions about the topic were at the start of the collaborative concept mapping task. For example, the maximum distance was found in group 3 between Participants 1 and 3 (4%). The minimum distance

found is in group 1, where Participants 2 and 3 shared 50% of their propositions. However, if the proposition was not added by the participant, the contribution of that specific proposition was halved. Individual contribution (row 4) is the *minimum* distance between each individual map and the group map during the collaborative activity in terms of number of propositions they have in common. For example,

Row 5 and 6 correspond to the indicators of *transactivity and interaction* with other student's objects. Row 7 was measured as the *maximum* percentage of propositions of the group concept map that were not present in any individual map (e.g. a maximum created knowledge of 71% for group 2, and a minimum of 11% for group 3).

Table 6-1 Measures of group activity process: 1) A group in which group members worked independently; 2) a balanced group; 3) a group with a "dominant" student and 4) a group with a "free-rider".

Groups:	1-Independent work		2-Balanced work		3-Dominant		4- Free-rider	
Propositions	55		14		27		20	
	Touch Med	Verbal Low	Touch Low	Verbal Med	Touch High	Verbal Med	Touch Med	Verbal Med
<b>1-Level of participation (group)</b>	817 <sup>touches</sup>	12 <sup>min</sup>	432 <sup>touches</sup>	22.6 <sup>min</sup>	1102 <sup>touches</sup>	27.4 <sup>min</sup>	1383 <sup>touches</sup>	23 <sup>min</sup>
a) Participant 1	Med-30%	Med-43%	High-45%	Med-29%	Med-23%	Low-14%	Med-37%	High-47%
b) Participant 2	Med-28%	Med-39%	Med-29%	Med-28%	Med-21%	Med-28%	High-51%	Med-37%
c) Participant 3	High-41%	Low-17%	Med-25%	High-42%	High-54%	High-56%	Low-10%	Low-15%
<b>2-Heterogeneity (Gini coeff.)</b>	0.30	0.29	0.27	0.16	0.35	0.44	0.50	0.34
<b>3-Individual map differences</b>								
a) P1 and P2	5%		14%		9%		21%	
b) P1 and P3	23%		8%		4%		20%	
c) P2 and P3	50%		17%		40%		35%	
<b>4-Individual contribution</b>								
a) Participant 1	55%		28%		30%		51%	
b) Participant 2	59%		55%		23%		53%	
c) Participant 3	54%		8%		54%		24%	
<b>5-Transactivity (avg p/student)</b>	1 links (SD =2)		7 links (SD =1)		10 links (SD =4)		8 links (SD =6)	
<b>6-Interaction (avg p/student)</b>	7 actions (SD =4)		36 actions (SD =27)		58 actions (SD =48)		28 actions (SD=22)	
<b>7-Knowledge building (max)</b>	45%		71%		11%		20%	

## 6.2.5. Discussion

Results indicate that groups diverged in interaction styles and presented diverse quantitative indicators. Four different types of groups could be described. These groups were chosen because they illustrate distinctive and interesting behaviours in the ways they decided to work.

### *Independent work / balanced work.*

This section compares two groups that showed opposite behaviour in terms of degree of collaboration. In the first group, students worked mostly separately without showing awareness of other's actions. They worked independently, giving some comments to the others about their artefact but mostly being engaged in their individual work. One student reminded the others that the objective of the task was to work collaboratively by generating an agreed upon concept map, but the others stated that they should reproduce their individual concept map at the tabletop first. Even when at least two students understood the instructions, they agreed not to collaborate as illustrated in the following excerpt (see Table 6-2).

Table 6-2 Example excerpt of a non collaborative situation

Time	Participant	Comment
5:15	P2	is not the final destination to have a final concept map? (after minutes working separately)
5:18	P3	Yeah
5:23	P1	no, just present it ours for each other? (P1 keeps working on its own)
5:24	P3	All of us should make just one graph (P3 stops working on the tabletop)
5:27	P2	one graph for all the concepts? (P2 keeps working on its own)
5:30	P3	yeah, all of us really need only one graph
(However, they continued working separately until the end of the activity)		

Interestingly, the measures of symmetry showed a rather balanced group work with the participation of each group member close to the overall average (average 272 touches and speaking time of 4 minutes per student). So, relying on just these indicators of symmetry is a limited view of the collaborative process of this group. The indicator of *transactivity* averaged just one link per student. This means that during the whole activity, on average, each student created just one link using a concept that other student added (3, 1 and 0 links for each student). They averaged seven actions per student performed on objects created by others. As a result, they ended up building three distinct concept maps at the tabletop and barely interacted with other's objects. Additionally, a high degree of contribution (54%) and knowledge building (45%) were observed. However, given the fact that they worked almost separately, facilitators may argue that this "created" knowledge cannot be attributed to the group work because they worked on three concept maps rather than just one group map.

By contrast, the second group performed better in terms of collaboration. Table 6-1 illustrates that the three member's participation was more balanced, especially for the verbal participation (Gini coefficients closer to 0, for touch=0.27 and verbal participation=0.16). In this case, even when their individual concept maps were not very similar (rows 3.a, b and c, e.g. 8% of similarity between the individual maps of participants 1 and 3) their indicators of *transactivity* and *interaction* with elements created by others were higher than group 1 (mean of 7 links and 36 actions per student). The following excerpt (Table 6-3) illustrates how balanced their conversation and the physical actions performed on their concept map were.

Table 6-3 Example excerpt of a non collaborative situation

Time	Participant	Comment
9:00	P3	alright! so..
9:02	P1	(moves the concept "Food" to the centre of the tabletop for everybody to discuss)
9:07	P1	So "Food" contains... (the proposition "Foods contains Fats" is already created)
9:10	P3	"Food" contains "Fats" and also contains "Proteins" so we join it to that link
9:11	P1	yeah (creates a new link between "Food" and "Proteins")
9:12	P2	Yeah
9:14	P3	what do we have there? (pointing at a region of the table closer to Participant 1)
9:14	P2	(creates a link between "Food" and "Balanced diet")
9:14	P1	(edits the linking words of the two propositions just created to "contains")

The level of verbal participation as a group was close to the total average across all groups. However, their effective work was relatively small (their group concept map contained only 14 propositions). A teacher could have encouraged them to consider including more of their individual propositions in the shared concept map. Nevertheless, this group scored the highest rank in *knowledge creation* (0.71). Figure 6-6 shows the difference between these two groups (graphs a and b in the figure) for the indicator of *interaction*. Each action performed by one student with the objects created by other student is represented as a horizontal line from the vertical axis that corresponds to the user who performs the action to the vertical line of the students who created the object that received such an action. Graph a) shows a small number of *interactions*. By contrast, graph b) shows that the interactions with other's objects started earlier during the group activity and the distribution was more balanced.

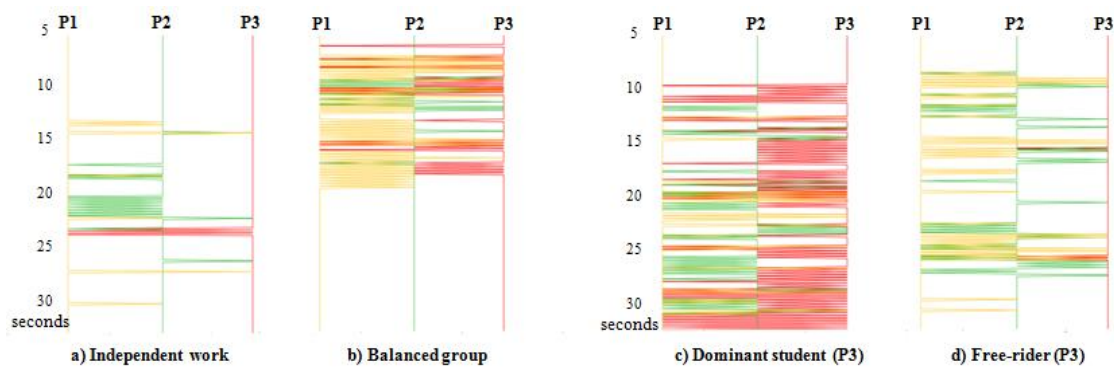


Figure 6-6 Graphical representation of interactions: each student's actions performed on elements created by others for a) group that showed independent work, b) balanced participation, c) a dominant student (P3) and d) a free-rider (P3). Each vertical axis represents one student (P1, P2 and P3 coloured in yellow, green and red).

*Dominant student / Free-rider.* In group 3, Participant 3 performed most of the changes to the group map, and controlled most of the decisions. Participant 3 performed more than 600 meaningful actions (while the two other group members performed less than 250 actions each) and he spoke for 16.6 minutes (around 60% of the total speaking time detected for the 3 participants). This asymmetry of participation was captured by the Gini coefficients (physical=0.35 and verbal participation=0.44). The *transactivity* and *interaction* measures were higher than in Group 2. However, these averages are skewed due to the dominance of participant 3 who used other's concepts to create links and built the shared concept map almost by himself (Participant 3 performed 113 actions on other's elements while the other two group members did only 41 and 21 actions respectively,  $M=58$  actions,  $SD=48$ ). Figure 6-6 (c) shows the *interaction* for this group. Participant 3 interacted with other's concepts to a greater extent than the other two students. As a result, the final group map had a low score for *knowledge building* because the final solution was very close to the individual map built by the dominating student (Maximum knowledge building = 0.11 and individual contribution of Participant 3 = 54%). Another important aspect is the connection between individual map distances and the contribution to the final map. It could be expected that if two learners have similar individual maps (in this case Participants 2 and 3 shared 40% of their propositions) the contribution of both participants would be higher if one added most of his links. However, the metrics are sensitive to this effect. In this case even when participant 3 added more than 54% of their individual propositions, Participant 2 added just 23% of their map.

By contrast, the fourth group had two learners who collaborated well to merge their ideas and they agreed on propositions (Participants 1 and 2). However, the third participant did not contribute to the group effort and had far lower levels of participation compared to other group members (free-riding effect) contributing only to 10% and 15% of the physical and verbal participation respectively (Participant 3 had only 62 touches and 3 minutes of speech during the 30 minutes). Due to the lack of participation of this participant compared with the two others, the symmetry of participation of the group was high (Gini coefficients: physical=0.50 and verbal participation=0.34). The indicators *transactivity* and *interaction* with other's objects were similar to other groups because the two collaborative participants worked together on the same task, building their propositions on the other's concepts and links (average *transactivity* of 9 concepts per person and interaction of 28 actions per person). Participant 3 only interacted three times with other's objects and created few propositions. Figure 6-6 (d) shows these three interactions between participant 3 (red) and objects created by Participant 2. It can also be seen that Participants 1 and 2 interacted with their objects and inclusively with the objects that were created by Participant 3.

## 6.2.6. Section Summary

This section explored novel ways to automatically generate group indicators that can describe various aspects of the collaborative knowledge construction and sharing processes. Results suggest that the quantitative information about student's interactions captured by COLLAID can complement qualitative assessments of collaboration obtained from observations. These results provide evidence that the indicators of collaboration discussed in this section can be used to build support tools that



can help teachers direct their attention more effectively to groups that appear to have non-ideal collaborative behaviour. This section explored the indicators of face-to-face verbal and physical participation, equity of the group, individual contribution to the final product, transactivity, interactions with other's objects, and the generation of new knowledge created during the collaborative sessions. The results of our small study **illustrate the feasibility and utility of producing group indicators that can make visible aspects of the collaborative learning process visible, in ways that are not easy to see in the final product.**

## 6.3. Visualisations of Collaboration at the Tabletop

This section presents the design and evaluation of a set of visualisations that reflects the activity of a small group of students building an artefact<sup>1</sup>. These visualisations can provide a mirror of learner's actions (touch/verbal participation radar), contributions (contribution chart) and the evolution of the artefact through the knowledge building process (evolution diagram). The aim is to determine the visualisation features that can provide useful information about group's collaboration at the tabletop. These visualisations seek to summarise and make visible the actions of the group members to help facilitators detect problems in group interactions. This first set of visualisations were validated by assessing whether teachers can answer key questions about *participation*, *contribution* and the *process* of the collaborative group's activity. The key contributions of this study are the design of these new group visualisations, the implementation of an automatic approach to produce these visual indicators in the context of our concept mapping learning environment and an evaluation which indicates that teachers can answer 4 of 5 key questions related to longitudinal equity and quantity of participation, contribution and collaboration in general.

### 6.3.1. The Learning Environment

The version of CMATE that was used in this study is our second prototype (see Section 0), in which each touch is logged and tracked by providing a moveable circular personal area on the tabletop for each participant. Users can *initiate* all actions just within the bounds of these areas. To perform actions on the concept map, participants move their personal area above the target element and then perform the actions. This technique increases the load of touches on the tabletop but provides customised personal concept/linking word lists for creating nodes, allows a more effective orientation of elements and also supports tracking of all the touches performed by each participant. The position of learners around the tablespots has been shown to have an effect on the division of labour spontaneously adopted by the learners (Jermann et al., 2009). Consequently, we had participants in pairs along both long sides of the rectangular tabletop (Figure 6-7, left). This gave each participant equal opportunity to participate, access the resources, and perform the full range of actions. Where the group had three participants, we had to settle for a slightly less ideal spatial disposition (Figure 6-7, right). The tabletop hardware technology used in this study was equivalent to that used in the study presented in Section 6.2.

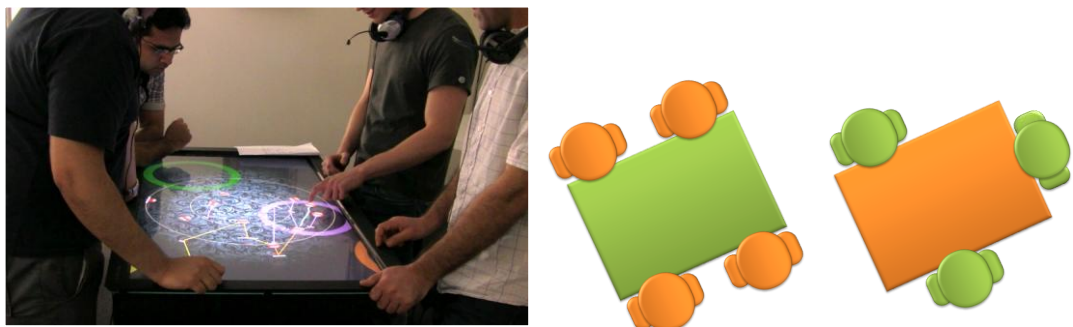


Figure 6-7 Tabletop concept mapping. Left: CMATE in action with 4 people, 2 at each long edge of the table. Right: Position of learners around the tabletop, with 4 students and with 3 students.

<sup>1</sup> Parts of this section have been published in the proceedings of CSCL2011 (Martinez-Maldonado et al., 2011d).



The study was run with 10 participants in 3 groups, each of 3 or 4 participants. All groups were asked to build concept maps individually at a desktop and then a group map at the tabletop, on the topic: *how does the water cycle work?* Similarly to the previous study setting, students were introduced on the concept mapping technique. Then they read a two page text on the water cycle and were asked to draw an individual concept map. After completing their concept maps, the group was asked to generate a group solution concept map at the tabletop.

### 6.3.2. Design of Visualisations

We now describe the four visualisations that were designed: the *touch and verbal Participation radars*, the *map contribution chart* and the *map evolution diagram*.

*Touch and verbal participation radars.*

This first visualisation was strongly influenced by the circular social proxies of Erickson (1999). We also drew on previous work in collaborative learning, with a focus on the learning impact of the equity of oral participation and decision making (Bachour et al., 2010). Based on these, and the procedure to study levels of participation on the tabletop proposed by Harris et. al. (2009), we chose to focus on two dimensions: the physical events on the tabletop, measured in terms of the quantity of touches; and time of verbal participation, measured in seconds. As a result, we designed a pair of radars: the radar of touch participation (see Figure 6-8, red shaded radars) and the radar of verbal participation (Figure 6-8, blue shaded radars). The time window for each visualisation shown in Figure 6-8 is the previous 5 minutes of activity. So for example at time 15, the radars show the number of events between minutes 10 and 15. Each coloured round marker corresponds to one learner at their circular personal space: orange, yellow, green and purple for participants 1, 2, 3 and 4 respectively. The position of these markers indicates the level of participation; the closer the marker is to the centre, the less active they were in the last five minutes. The positions of the round markers are not associated with any specific physical disposition of learners around the tabletop.

The shape of the radars depict the symmetry of activity, an important aspect of collaboration (Dillenbourg, 1998). For example if there are 4 learners, a perfectly symmetric square indicates that the number of touches or the talking time are the same for each learner. In the radars shown at the right of Figure 6-8 (at minute 25), we can observe that the student corresponding to the yellow marker (at 3 o'clock) did not touch the tabletop at all but did most of the talking. This could possibly be a clue that this student was influencing the actions of others by talking but, without further information, it could equally mean that he/she was engaged in a conversation that had nothing to do with the task.

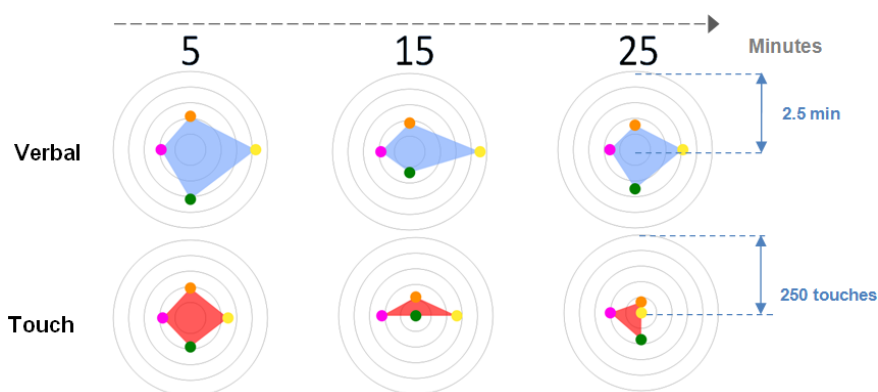


Figure 6-8 Participation radars. Left: First five minutes. Centre: Between minute 10 and 15. Right: Between minute 20 and 25.

These radars can provide information to compare groups. Figure 6-9 shows three pairs of radars for a collaborative group with 4 students (left) and a non collaborative group with 3 students (right). It can also be observed that the parameters used to display the visualisations change according to the maximum amount of activity calculated at a determined point in time. Comparing the visualisations shown in Figure 6-8 and Figure 6-9 there is a difference in the metrics used to draw

the graphs; 2.5 minutes against 1.5 minutes of talk, and 250 against 100 touches respectively. In this example, the visualisations indicate that the collaborative group had more verbal participation but a low level of physical actions at the tabletop (see the pairs of radars 1, 2 and 3 at the left of the Figure 6-9). By contrast, the members of the non collaborative group performed physical actions without talking much (pairs of radars 4, 5 and 6).

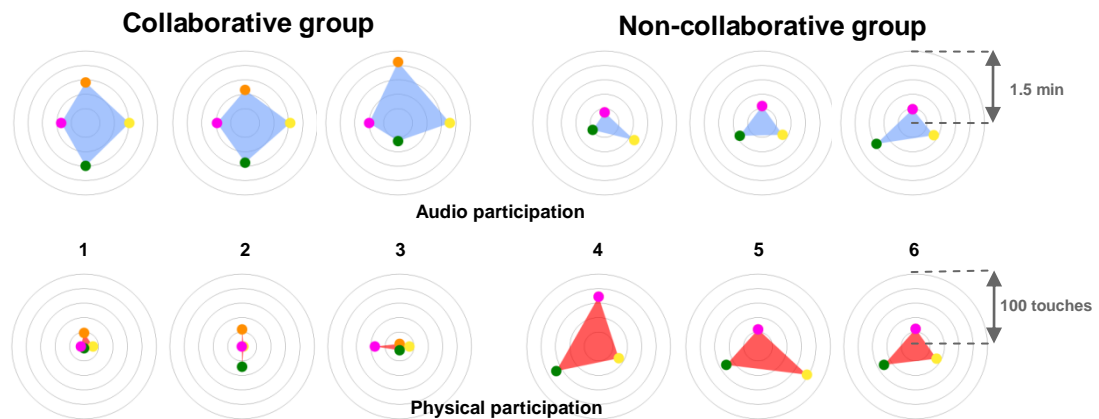


Figure 6-9 Radars of activity for three different episodes, for two groups

#### Contribution Chart

Concept mapping has the potential to drive collaboration because it provides an externalisation of each learner's different perspective (Tergan, 2005). Based on this we designed the contribution chart, which shows the proportion of actions from each team member that resulted in a change in the collaborative artefact. The actions which add substantial knowledge to the map are the creation, editing and deletion of nodes. The map contribution chart gives an overview visualisation of the proportion of these actions that each participant made.

Figure 6-10 shows three of these charts for the same group, at minutes 5, 10 and 20, and also shows the total number of concepts and links created in the group artefact. The design of this visualisation aims to show if any of the participant's perspectives is leading the construction of the concept map or if they are equitably contributing to it. This visualisation complements the radar of participation by indicating the amount of the activity that has indeed made a substantial impact on the group artefact. For instance, the first chart in Figure 6-10 (at minute 5) shows that one student (in pink at the top) contributed about half the concept map's elements, two students (green and yellow) contributed a quarter, and one (red, at the right) much less than the others. At time 10, however, we can observe that the other three learners increased their contribution greatly (especially yellow and red), and later on (at time 20), the same student (pink) contributed the most to the artefact again. The relative dimension of the contribution between two given times is indicated by the overall number of links and concepts and the relative size of the charts.

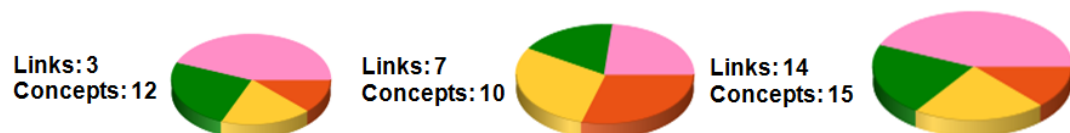


Figure 6-10 Contribution chart. Left: After 5 minutes. Centre: After 10 minutes. Right: After 20 minutes.

#### Evolution Diagram

The third visualisation is the Evolution Diagram (Figure 6-11). It shows the key temporal events in the group concept map. The vertical axis shows the number of propositions added to the group concept map and the horizontal axis represents time measured in minutes. The graph has two

sparklines: i) the upper blue line includes coloured circles indicating addition of each proposition by a given participant; ii) the lower red line shows the number of propositions that match those in the master concept map (created by the teacher). So, the upper line shows the total number of propositions and the lower line shows how many of these propositions match the expert map. To calculate the distance between the group map and the master map, we use an automatic open-ended scoring technique based on Pathfinder associative networks (Taricani and Clariana, 2006).

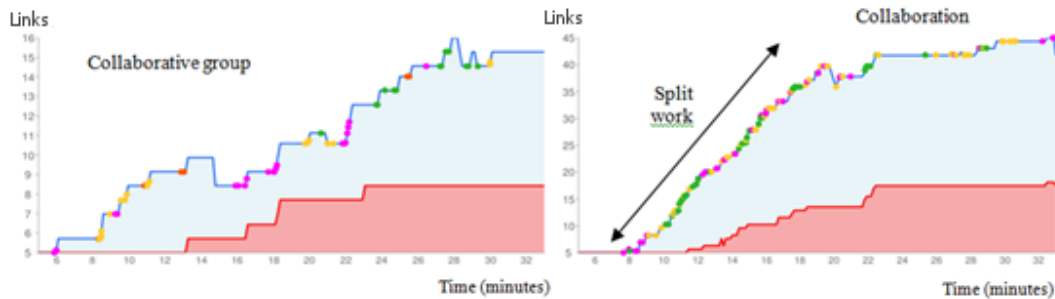


Figure 6-11 Map evolution diagram. Left: A group of four learners working collaboratively most of time. Right: A group of three learners who divided the work during the first 20 minutes.

In the upper line, the coloured markers represent the user who added the proposition(s). In Figure 6-11 (left), the visualisation shows that the group has worked for more than thirty minutes and has created 16 propositions. Observing the purple markers (User 4) we see that this user created more propositions that were present in the master map, as the purple markers coincide with signs of progress of the group map towards the master map. In contrast, the map evolution diagram on the right shows that, up to Minute 20, this group added many links but these actions did not result in any matching with the expert map, suggesting that users were working independently, each working on adding a high number of propositions at the same time. Note that, in this visualisation, the similarity with a master map is not used to score the group map but just as an indicator of how many of the group's propositions match those in the teacher's perspective.

### 6.3.3. Evaluation

The evaluation of the visualisations consists of asking a number of facilitators to give answers to a set of questions regarding the equity of participation, quantity of participation, collaboration, equity of intellectual contribution of the members of the group (Dillenbourg, 1998; Stahl, 2006) and the process of the concept map construction. We expected that the support offered by our visualisations should make visible some facets of the collaborative process to facilitators and hence lead to improve the feedback they can offer to the group. Specifically, we aimed to evaluate five hypotheses: The set of visualisations provide useful information to teachers about:

- (H1) the *equity in the roles and participation* of group members;
- (H2) the *amount of participation* of the group members;
- (H3) the group in terms of *collaboration*;
- (H4) the *equity of intellectual contribution* of group members;
- (H5) the *creation process* of the map in terms of the relative contributions of group members and the effectiveness of the group work.

To assess these hypotheses, we conducted evaluation sessions with five different experienced facilitators to test if the information provided by the visualisations was meaningful in terms of our hypotheses (Nielsen, 2000). We provided them with a set of the visualisations generated from the tabletop sessions of two differentiated groups: A) a collaborative group, and B) a group where learners worked independently. One example set of visualisations shown to teachers is illustrated Figure 6-12. These visualisations included: snapshots of the Radars of Participation and Contribution Chart corresponding to minutes 5, 10, 15, 20, 25 and 30, the Evolution Diagram and the final group

concept map. They were arranged on a piece of paper as a mock-up of a teacher's dashboard. We also provided the final maps, from both the individual and collaborative stages. We invited the facilitators to respond to a set of questions regarding the equity of participation, quantity of participation, the collaboration, the equity of intellectual contribution of the group members and the usefulness of the visualisations to depict the creation map process in terms of contribution and group work. Each question corresponded to one of the hypotheses posed above, and they were answered on a 7-point Likert scale in which 1 represents strong disagreement and 7 strong agreement. We allowed them to mark a question as "unanswered" if the visualisations did not give enough support for a decision. We asked the participants to justify their responses and state which visualisations they used.

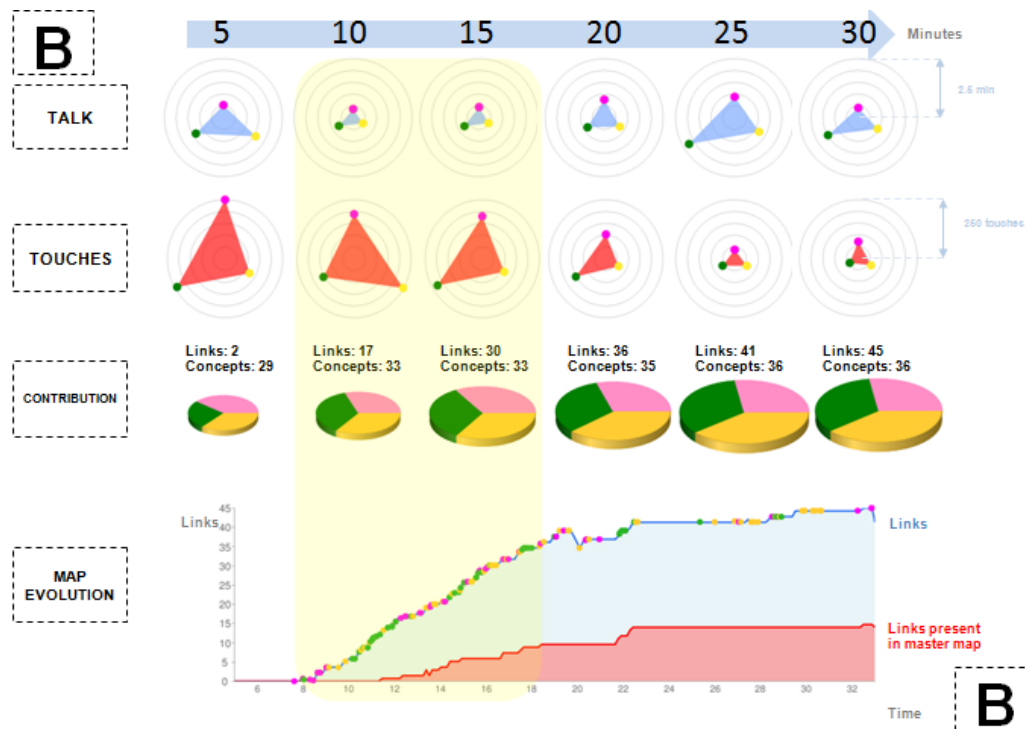


Figure 6-12 Initial dashboard mock-up: material provided to teachers to assess visualisations of a group of students.

#### Inspection of the session videos.

As a basis for comparing the information inferred by the facilitators from the visualisations, we inspected the video recordings of each group's session. We describe them now. *Group A* was highly collaborative from the beginning. They focused on working collaboratively and they built the concept map as a group. They never divided the task. They discussed every single action that each group member performed. They worked in parallel for brief periods but never losing awareness of other's actions. They added key concepts and links, and tried to eliminate redundant concepts by "generalising" them to come up with a clearer map. It is really important to point out that before finishing their session they realised that the shape of their map should be circular, given that the water cycle is indeed one. Notably, in the individual maps, none of the students drew a cyclic map.

*Group B* worked independently from the beginning and then started collaborating at the second half of the session. At the very beginning, they added many concepts and links to the tabletop, explaining and giving brief comments to the others about their actions, which concepts they considered important and asking if they had already added specific concepts that they may use. The concept map at the tabletop, as shown at *left* of Figure 6-13, is itself a visual aid because it highlights the different propositions added by each participant. This feature proved to be really useful for this group. They divided the task and worked in parallel without collaborating with other group members. This happened until minute 20. At minute 21 one member of the group said: "your area has more green colour, mine is purple and yours more yellow ... we really came up with three

*distinct parts. There should be more links between them*". They tried to collaborate after minute 20. The evolution diagram shows this change in the group's behaviour (*right* of Figure 6-13). Then they worked together to decide which links could best connect the different three main areas of the concept map. However, they ran out of time and the final map was complex and was a poor response to the task.

### 6.3.4. Results

All the facilitators were able to easily understand the visualisations and complete the questionnaire without difficulty. They were highly engaged in the inspection of the visualisations, and expressed their thoughts verbally, permitting the experimenter to take note of which visualisations influenced their comments. The facilitators neither watched the videos nor had access to any summary of what happened during the sessions. They inspected the visualisations carefully before giving an answer to each question for both groups, A and B. To look for an explanation of the acceptance or rejection of each hypothesis, we validated the responses to the questions at two levels. Firstly, we refute a hypothesis if its respective question could not be answered by at least two facilitators. This filter refutes a hypothesis if the facilitators could not find evidence from the visualisations to give an answer. Then, the next step was to ascertain whether their answers matched the observations from video recordings of the sessions. Table 6-1 summarises the questionnaire responses. Columns Q1, Q2 and Q3 were used to generate the graph of Figure 6-13 (*right*). Table 6-2 summarises which visualisations the facilitators used to give an answer to each question.

(H1) *These visualisations provide useful information about the equity in the roles and participation of the group members.* The focus of this hypothesis is to assess whether the visualisations show the symmetry of participation of the group members (Dillenbourg, 1998). All the facilitators used both the radars of voice and touch to answer this question (see Table 6-2). For group A, the participation was moderately equitable but one participant slightly dominated most of the verbal participation. This can be observed in Figure 6-8. In Figure 6-13 (*right*, see Q1A) we see that in general the responses of the facilitators did not confirm that the group was either symmetric or asymmetric. In general, the facilitators judged group B to be symmetric (see *right* of Figure 6-13, Q1B). In fact, the video recordings showed that group B members mostly worked in parallel and they did not influence each other. Thus we accept the usefulness of the radars of physical and audible participation based on the direct observations of the facilitators. The facilitators remarked that the coloured shaded radars and the concentric circles were useful to quickly detect if the participation of a group was symmetric or not.

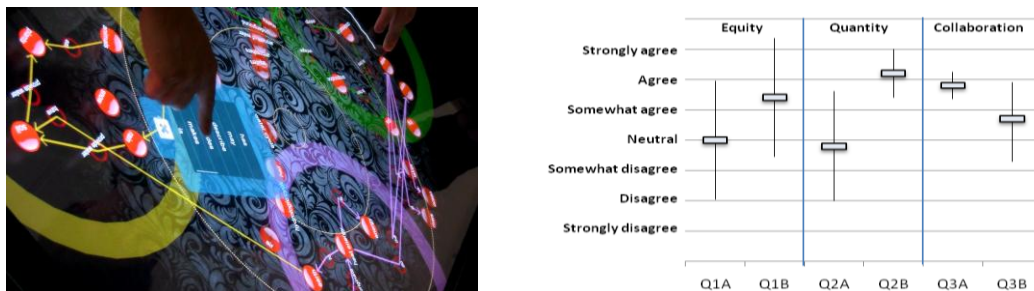


Figure 6-13 Left: The coloured links of the map as a visual indicator of contribution itself. Right: Overview of the results of the questions related to: equity of participation (Q1A for group A and Q1B for group B), quantity of participation (Q2A, Q2B) and collaboration (Q3A, Q3B)

(H2) *These visualisations provide useful information about quantity of participation of the group members.* The focus of this hypothesis is to assess if the visualisations depict the quantity and equity of participation of the group members; therefore, it is also related to H1. However, in this case, four out of five facilitators used the Contribution Chart in addition to the radars of Participation and the Map Evolution Diagram to answer this question. Group A was reluctant to do physical actions compared with Group B. They focused more on the discussion and negotiation around each proposition to be created and each element to be deleted. By contrast, Group B divided the task and added a large number of propositions. Indeed, the facilitators strongly agreed that in general group B

members participated in an equitable way. For group A they noticed that the members did not perform many actions and some evaluators commented that they were talking too much and working very slowly, at the physical level (*right* of Figure 6-13, Q2A and Q2B). Therefore, we accept the usefulness of the map Contribution Chart in conjunction with the Radars of Participation and the Evolution Diagram because they gave insights to facilitators of the extent of learner's participation.

Table 6-1 Summary of the questionnaire responses. Columns: questions asked to the evaluators.

Group A	Q1 Equity	Q2 Quantity	Q3 Collaboration	Q4 Contribution	Q5 Process
AVG	4	3.8	5.8	6	6.25
SD	1.95	1.8	0.45	*	0.5
Lickert	neutral	neutral	agree	agree	agree
Group B					
AVG	5.4	6.2	4.5	6	6.25
SD	1.95	0.8	1.2	*	0.5
Lickert	agree	agree	agree	agree	agree

Rows: AVG: Average of 7-point Likert scale answers. SD: Standard deviation. \*Not all facilitators answered Q4.

(H3) *These visualisations provide useful information about the group in terms of collaboration.*

The focus of this hypothesis is to assess if the visualisations can offer hints to the facilitators to indicate whether the group was collaborative or not. To answer the question related to this hypothesis, the facilitators used all the visualisations including the final product map. All the evaluators agreed that group A was collaborative, even though their final product was a small concept map. Moreover, the facilitators considered that in this group the students interacted with others based on the high levels of talking observed in the verbal radars and the sparse *add link* events shown in the Evolution Diagram (*left* of Figure 6-11). In the case of Group B three of five facilitators concluded that the group divided the work most of the time given the low levels of talking and the creation of many links in a short time window (*right* of Figure 6-11). Moreover, the facilitators agreed that the group tried to collaborate in some way before the end of their activity (*right* of Figure 6-13, Q3B).

(H4) *These visualisations provide useful information about the equity of intellectual contribution of the group members.* The purpose of this hypothesis is to assess if the facilitator considers that the content of the concept map reflects intellectual contribution of each member of the group. We refute this hypothesis given the fact that just one of the five facilitators responded to the question related to it (see Table 6-2). All of them tried to infer intellectual contribution based on the Contribution Chart and the Radar of Voice participation, but afterwards, they concluded that it is difficult to infer the intellectual contribution without knowing the content of the utterances. Indeed, new knowledge is created through the content of the discourse of the group (Stahl, 2006).

Table 6-2 Visualisations that were used for the facilitators to answer each question

Q	Evaluators				
	1	2	3	4	5
1	Radars – Chart	Radars – Chart	Radars - Chart	Radars - Chart	Radar (t) - Chart
2	Radars – Chart	Radars – Chart	Radars	Evolution map	Radars - Chart
3	Final product - Evolution map	Radars – Chart	Radars	Final product	Radars
4	X	Chart	X	X	X
5	Radar (v) - Evolution map	Radars	X	All	Radars

Clustering results. Cluster-0 (C), Cluster-1 (M), Cluster-2 (NC).

(H5) *These visualisations provide useful information about the creation process of the map in terms of the relative contributions of group members and the effectiveness of the group work.* We validated this hypothesis by the direct answers to the corresponding question. All facilitators



somewhat agreed with the usefulness of the visualisations because they provide information about the process of map creation in terms of the physical and verbal actions.

Overall the facilitators could answer four of the five questions. These give insights into the usefulness of such tools for monitoring the collaborative situation at the tabletop even when the facilitator has the opportunity to observe the actions of the group in situ. Thus, the visualisations aim to complement the qualitative function of facilitators by providing quantitative insights about the group. Even when the results match well with our qualitative observations of the video, for equity, quantity, and the most important, the presence of real collaboration, the goal of the visualisations is to aid the qualitative results, not to take its place (Stahl, 2006).

### 6.3.5. Section Summary

This section presented a set of visualisations that externalise the activity of groups working together at the tabletop to build a group artefact. The Participation Radars provide a mirror of learner's actions both verbal and physical. The Contribution Chart gives an indication of the extent of each learner's contributions to the group artefact. The Evolution Diagram depicts the building process of the artefact relating this to a master artefact and with each participant's contributions. The study involved the participation of five facilitators analysing two groups only. This experimental design is appropriate for a first assessment of the usability, understand-ability and potential usefulness of these classes of visualisations. **These visualisations trace different aspects of a group, and the combination of the three visualisations with the final group artefact can help the facilitator better understand the nature of the collaboration** of each group.

## 6.4. Teacher's Interactive Dashboard

This section presents a teacher-driven design, implementation, and evaluation of a dashboard for guiding teacher's attention by showing summaries of *real-time* data captured from a tabletop environment<sup>1</sup>. This vision is illustrated in Figure 6-14 (left). Stephen Few (2006) defines dashboards as "*a visual display of the most important information needed to achieve one or more objectives; consolidated on a single screen so the information can be monitored at a glance*". Our dashboard shows a set of visual indicators of collaborative activity generated by means of group models and a data mining technique exploiting tabletop data including: amount and symmetry of learner's physical and verbal activity, the progress of the group towards the goal, the interactions among learners, and domain specific indicators. The main goal is to help teachers gain awareness by visualising selected information that would otherwise remain invisible so they can determine which groups need their attention right away and whether or not to intervene.



Figure 6-14 Class view of the teacher's dashboard displayed on a handheld device while a group of students build a concept map.

This work introduced a novel approach, that goes beyond previous work in the area as of learner models and collaborative learning data analysis (refer to Sections 2.3.4 and 2.4.1), by

<sup>1</sup> Parts of this section have been published in the proceedings of ITS2012 – Intelligent Tutoring Systems (Martinez-Maldonado et al., 2012f).

modelling and visualising aspects of collaboration that are produced from the unobtrusive capture of group member's interactions at an interactive tabletop environment. Additionally, this approach is specifically focused on supporting teachers.

#### 6.4.1. The Learning Environment

This study used an updated version of a collaborative concept mapping tabletop application, compared with the one used in the study described in the previous section (Section 6.3). This is the complete version of CMATE (see Section 0). Twelve university-level students participated in this study. They were assigned to groups of three and knew each other. Similarly to the study presented in the previous section, first, learners were asked to read the same text about the learning domain (healthy nutrition in this case) and build their individual concept maps in private using CmapTools. Then, learners came to the tabletop to integrate their perspectives into a collaborative concept map. The activity was semi-structured in four stages: i) individual concept mapping (external to the tabletop); ii) collaborative brainstorming of the concepts for the joint map; iii) adding propositions that learners had in common, and iv) the discussion phase, where learners create the rest of the propositions, by negotiating different views. They had 30 minutes for building individual maps (stage i) and up to 30 minutes for the collaborative stage at the tabletop (stages i, ii and iii; 5, 5 and 20 minutes respectively). All sessions were video recorded. This version of CMATE was connected to COLLAID (Section 5.4) which includes the overhead depth sensor to track the position of each user and automatically identify who did each touch; and the microphone array located above the tabletop to distinguish who is speaking.

#### 6.4.2. The Interactive Teacher's Dashboard

It is challenging to define ways to present the information of group collaboration in a manner that is easily understood by and useful for educators. For this reason we decided to include teachers, experienced in classroom collaboration, in early stages of the dashboard design. Features that classroom experts believed should be in a truly effective awareness tool included those for: identifying learners, those who are not contributing to the group who are dominating and controlling the activity; groups that work independently; or that do not understand the task (Section 6.3).

The dashboard was designed to enable teachers to determine whether groups or individual learners need attention. Four teachers were involved in the *teacher-driven* design process that consisted of a series of unstructured interviews, prototypes and empirical evaluations of both the visualisations and the structure of the dashboard (partly from the results of the study described in Section 6.3). The final result was a dashboard with 2 levels of detail: i) the *class level*, shows very summarised information about each of the groups so teachers can use it in *real-time* to see several groups at once during a classroom session, and ii) the *detailed group level*, that permits in depth exploration of a specific group's activity.

#### 6.4.3. The Class Level: Aggregated Summaries

The *class level* of the dashboard aims to give minimal information needed for a teacher to gain an overview of the overall activity of each group. This layer displays sets of three visualisations per group. We now explain the design of each of these.

##### *Indicator of collaboration.*

This visualisation shows the "level of collaboration" detected by the system. It is based on the model developed using the data mining prediction Best-First tree algorithm presented in Section 4.2. This algorithm was selected as it offered the second best accuracy and the coding of the resulting model was easier to implement (in the form of a decision tree). It classifies each block of half a minute of activity according to a number of features that can be captured from collocated settings. They are: number of active participants in verbal discussions, amount of speech, number of touches and symmetry of activity measured with an indicator of dispersion (Gini coefficient). The system labels each 30 second episode as one of three possible values: Collaborative, Non-collaborative, or Average. The visualisation shows the accumulation of these labelled episodes. The arrow bends to



the right if there are more *collaborative* episodes or to the left if there are more *non collaborative* episodes (refer to Figure 6-15-1).

#### *Graph of interaction with other's objects.*

Studies with students working at tabletops have confirmed that interacting with what other's have done may trigger further discussion that is beneficial for collaboration (Fleck et al., 2009). This display models the cumulated number of interactions by each learner with other student's objects at the tabletop (Figure 6-15-2). The size of the circles indicates the amount of physical activity (touches) by each learner. The width of the lines that link these circles represents the number of actions that the learners performed on the concepts or links created by other learners.



Figure 6-15 Overview visualisations. Left: a balanced group (Group A). Right: a group in which one member (red circles) was completely disengaged from the activity (Group D).

#### *Mixed radar of participation.*

Groups in which learners participate asymmetrically are often associated to cases of free-riding or disengagement, while collaborative groups tend to allow the contribution of all members (Dillenbourg, 1998). Inspired by our designs presented in Section 6.3.2, this radar models the accumulated amount and symmetry of physical and verbal participation (Figure 6-15-3). The triangles (red and blue) depict the number of touches and amount of speech by each learner. Each coloured circle represents a student. The closer the corner of the triangle is to the circle, the more that student was participating. If the triangle is equilateral, learners participated equally. This visualisation clearly derives from the ones presented in the previous section (Section 6.3.2).

The visualisations of three groups working simultaneously can be displayed on a handheld device as it is shown in Figure 6-16.

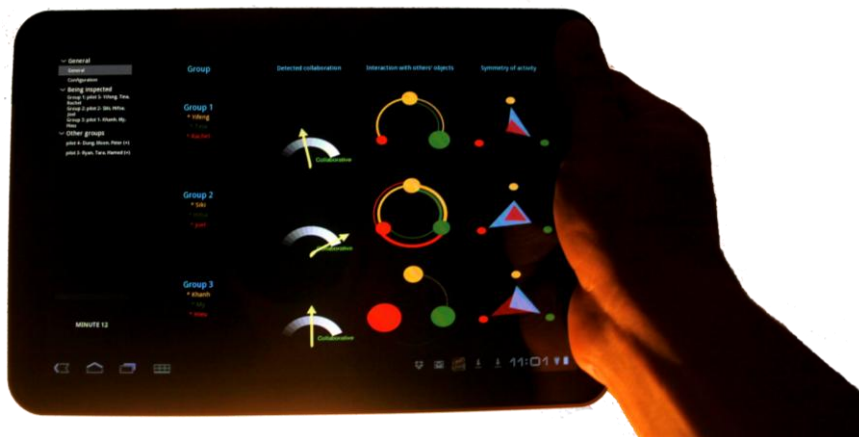


Figure 6-16 The teacher's dashboard: the class level.

#### 6.4.4. The Detailed Group Level: Specific Group Summaries.

This level shows information over time for *post-mortem* analysis. It can be accessed by touching the set of visualisations of a specific group in the *class level*. It includes the next five visualisation types.

### Evolution of the group map.

Inspired by our designs presented in Section 6.3.2, this visualisation shows the contributions of group members towards the group map, by displaying the number of propositions (links) created and their authors, along the time line (Figure 6-17). The small coloured circles indicate a “create link” event generated by the learner identified by that colour. In this way a teacher can become aware of dominant participants, see patterns of alternating contributions or whether all members contribute to the concept map evenly. The red flags (C, L) indicate the stages that students explicitly started: The first stage is brainstorming starting from minute 0 (not flagged). C= adding propositions learners have in *Common*, L= Main *Linking* phase. This is the only visualisation of the dashboard that is specific to the concept mapping task. In this case, as no master concept map was provided, there was no lower red line showing the number of propositions that match those in the student’s map.

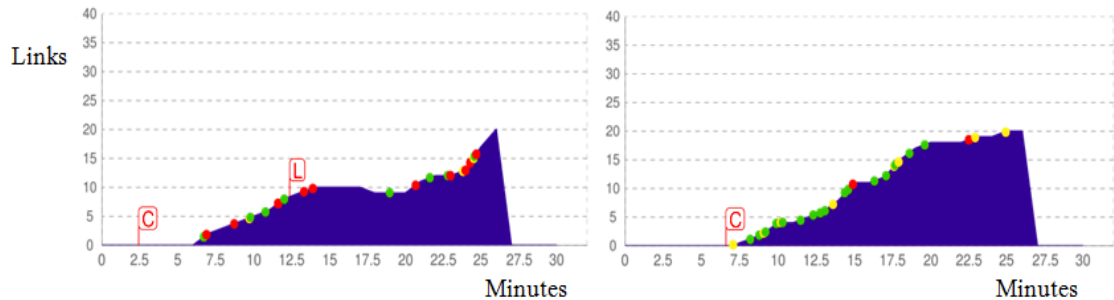


Figure 6-17 Evolution of the group map. Left: A group with a dominant student (red) and a low participant student (yellow) (Group C). Right: A group with a low participant (red) (Group D).

### Timeline of interaction with other learner’s objects.

This visualisation shows the amount of interaction by each learner with other’s objects. Each coloured horizontal line represents a learner’s timeline. Each vertical line represents an interaction of that learner with other learner’s objects. Figure 6-18 (left) presents the interactions of a group in which one learner (Alice, red coloured) dominated the physical interactions with her peers (Bob and Carl, green and yellow). Figure 6-18 (right) shows a group where learners rarely built upon other’s ideas, as there are very few interactions.

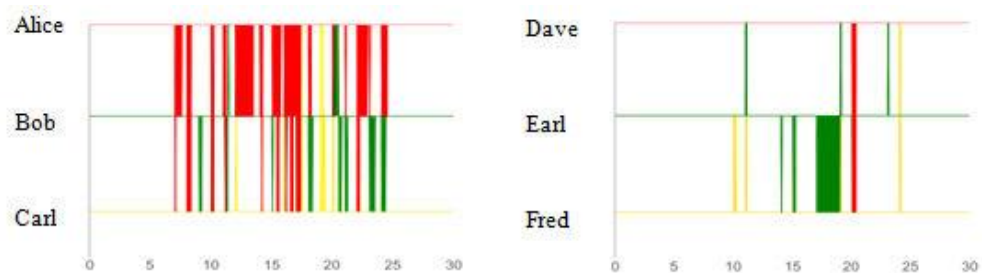


Figure 6-18 Timeline of interaction with other learner’s objects. Left: A group with a dominant learner (Group C). Right: group members that worked independently (Group B).

### Radars of verbal and physical participation in the timeline.

Completely extracted from the study presented in Section 6.2, these visualisations model the amount and symmetry of verbal (Row 1, Figure 6-19) and physical participation (Row 2, Figure 6-19) of each group member. Similarly to the cumulative radars described in the previous section, if the corner of the triangle is closer to the centre (black dot), that means the corresponding learner’s activity was low. Refer to Section 6.3.2 for full description.

### Contribution charts.

These visualisations model the dimension of the concept map in the tabletop in terms of propositions. They also show the distribution of the individual contribution to the group concept

map. The size of the charts indicates the number of links in the concept map. In the dashboard, these visualisations cover 4-5 minutes of activity. Therefore multiple visualisations are shown in the timeline (Row 3, Figure 6-19). Refer to Section 6.3.2 for full description.

The visualisations of a specific group can be displayed on a handheld device as it is shown in Figure 6-19.



Figure 6-19 The teacher's dashboard: the detailed group level.

### 6.4.5. Evaluation

We aimed to evaluate two research questions: (Q1) *Is the class level of the dashboard useful for teachers to decide when to intervene or which groups need their attention?* (Q2) *Which visualisations (at both levels) do teachers use to decide whether groups need attention?* Eight teachers experienced in small group classroom collaboration, at university-level, participated in the evaluation sessions. None had been involved in the design of the dashboard. The data recorded from four groups, each with three students, was used. *The 4 groups were cross-distributed among teachers so that each teacher monitored 3 groups at the same time and each group was monitored by 6 teachers.* The system simulated the *real-time* generation of data for the teacher, as if he or she was monitoring three groups during 30 minutes. This version of the dashboard presents up to three groups at the same time.

In parallel, each group video was manually analysed by an external researcher to diagnose group's collaboration and provide a baseline reference. Based on these observations, groups can be described as follows: Group A performed best in terms of collaboration. Students discussed their ideas, worked together to build the group concept map. They completed the task sooner than the other groups and their final solution was simpler. By contrast, members of Group B worked independently most of the time, building three different concept maps rather than combining perspectives into a shared map. Group C was distinguished by the dominance of a single student, who lead the discussion, took most of the decisions and ended up building most of the group map without considering other's perspectives. In Group D, only two learners collaborated to merge their ideas. The third learner did not contribute to the group effort and had lower levels of participation – *free-riding*.

The evaluation recreated the *classroom orchestration* loop documented by Dillenbourg *et. al.* (2011): teachers monitor the classroom, compare it to some desirable state, and intervene to mentor students. This was adopted as follows:

1. First, teachers were asked to think aloud as they were looking at the *class level* of the dashboard, verbalising their perception of each visualisation (Figure 6-20, 1).
2. Then, they were asked to state whether each group was collaborating.

3. As appropriate, they would select the visualisations that indicated that a group might have *issues* in terms of collaboration.
4. As appropriate, they would choose one group (or none) that they would attend to, indicating which visualisations helped them to take such decision.
5. As a response, the system drills down from the *class level* to the selected *detailed group level* of the dashboard (Figure 6-20, transition from 1 to 2 considered as **Attention**).
6. Then, teachers were requested to think aloud, stating the visualisations that helped them to confirm possible *anomalies* and whether they would talk with the group members or provide corrective feedback (Figure 6-20, 2). If the teacher decided to intervene they had to wait at least 2 minutes in this layer without viewing other groups (simulating the time taken to talk with the group, this is considered as an **Intervention**).

Teachers followed this loop throughout the 30 minutes duration of the trials, the actual average duration of each group activity, simulating parallelism (Figure 6-20, transitions from 3 to N). Finally, they were asked to answer a questionnaire to validate that they understood the visualisations. Data captured from the teacher dashboard usage sessions were recorded and analysed.

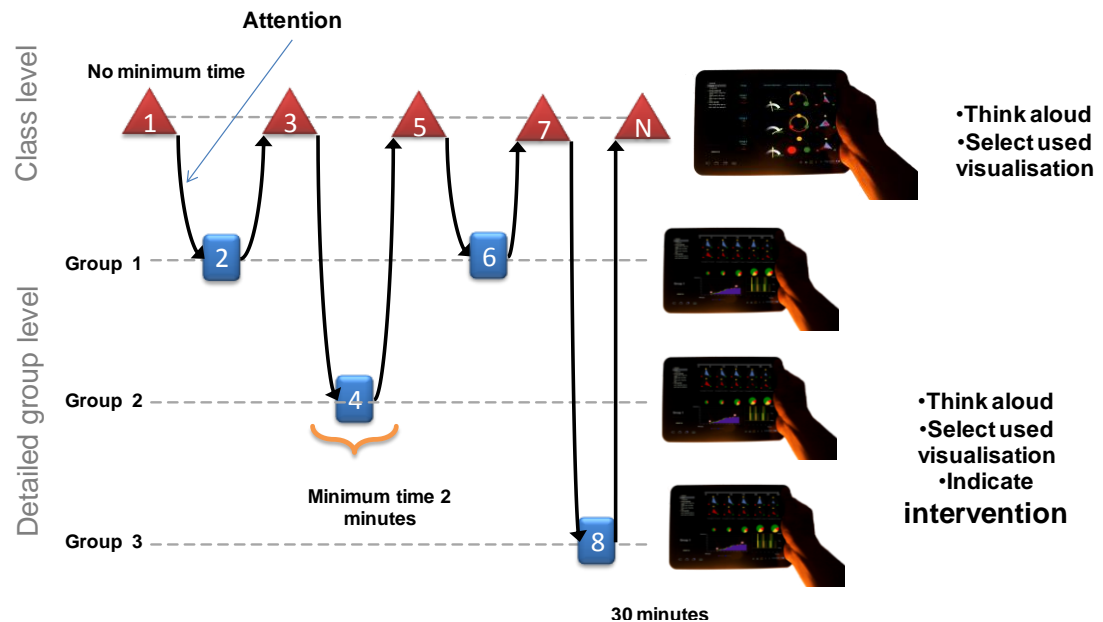


Figure 6-20 Example of the orchestration tool emulated in the dashboard's evaluation.

#### 6.4.6. Results and Discussion

(Q1) *Is the class level of the dashboard useful for teachers to decide when to intervene or which groups need their attention?* This research question drove the study. Our objective is to help teachers recognise potential issues within the groups so they can be more aware about which group needs attention. Table 6-3 shows the two main evaluation aspects: which group teachers would visit next and why (*attention*), and if they would either intervene or let the group continue working (*intervention*). During the experiment *attention* was indicated when teachers navigated from the *class level* to the *detailed group level* of the dashboard. *Interventions* were indicated when, after analysing the group level of the dashboard, teachers felt that the group still needed to take corrective actions to improve collaboration.

Results indicated that teachers would focus most of their attention on groups B and D (investing 44% and 40% of their time on average on them). They correctly identified independent work and the presence of a free-rider as their major issues. They indicated interventions would have served to encourage students to work more collaboratively and share their ideas with others (on

average 4 interventions out of 7 points of attention and 3 interventions out of 6 points of attention respectively per teacher). Group C gained a similar level of attention (13% of intervention out of the 31% of attention per teacher). In fact, the difference in the *attention* across these three groups was not significant (t-test,  $p > 0.05$ ). However, for all of the teachers, Group A was clearly performing well and teachers would not have intervened (average of 2 visits and 0.7 interventions per teacher). The difference between the attention provided to other groups and Group A was statistically significant ( $t(10)=6.6$ ,  $p < .00027$ , two-tailed). Inter-teacher agreement was calculated to examine how different the observations were. Table 6-3, Column k (Cohen's kappa) shows that the 6 teachers who monitored each group agreed on *which* group needed intervention and *when* they needed it either at the beginning, in the middle or by the end of the task-  $k > 0.4$ .

Table 6-3 Teachers attention and interventions per group. Att= Average number of times each tutor decided to monitor that group. Att%=Average proportion of moments dedicated to that group. Int=Average number of interventions. Int%=Average proportion of interventions. k= Inter teacher agreement (Cohen's kappa).

Group	Attention		Interventions		K	Observations based on the videos
	Att	Att%	Int	Int%		
A	2 (s=1)	15% (s=7)	1 (s=0.5)	4% (s=3.4)	0.7	Even group
B	7 (s=2)	44% (s=7)	4 (s=1.4)	21% (s=6)	0.4	Independent work
C	5 (s=1)	31% (s=6)	2 (s=0.6)	13% (s=3)	0.5	Dominant student
D	6 (s=3)	40% (s=13)	3 (s=1.7)	19% (s=8)	0.5	Free-rider

(Q2) *Which visualisations (at both levels) do teachers use to decide whether groups need attention?* Based on the think aloud analysis of the *class level* visualisations, we found that teachers agreed on the usefulness of the *mixed radar of participation* and the *chart of interactions with other's objects* graphs. These provided them with enough information to identify possible problems within certain groups. Some teachers indicated that the third graph, *indicator of detected collaboration*, was useful only to *confirm* their observations using the first two charts. Table 6-4 shows that teachers obtained more information from the two first visualisations (85 and 65 detected issues) and started to use them from the beginning of the activity. They identified the main anomalies of groups B, C and D describing the main problems with the groups: independent work and a low participant for Group B, a dominant student in Group C and a free-rider in Group D. They were not concerned about Group A (Table 6-3, 15% for *Attention*). Four out of 6 teachers indicated that Group A progressed quickly and finished the activity quickly, so in a real scenario they would have encouraged them to explore more ideas to complete their work. Teachers indicated that the detailed timeline level of the dashboard provided information about the *progress* of each group. All agreed that this level would become an important tool for after-class analysis but the *class level* of the dashboard provides enough information to identify possible anomalies during a classroom session.

Table 6-4 Potential group anomalies identified by teachers using each visualisation.

Visualisation	Total	Min 10	Min 20	Min 30
<b>Level 1 – Class</b>				
Mixed radar of participation (audio and touches)	85	36	23	26
Chart of interactions with other's objects	65	18	29	18
Indicator of detected collaboration	26	8	6	12
<b>Level 2 – Detailed group</b>				
Evolution of the group map	22	1	8	13
Timeline of interactions with other's objects	35	3	18	14
Radars of verbal participation in the timeline	31	8	13	10
Radars of physical participation in the timeline	36	7	15	14
Contribution charts	26	7	7	12

Table 6-4 shows that teachers tended to use all the *timeline* visualisations in combination to detect *issues* (usage between 22 and 36). However, it does not provide useful information during the first 10 minutes of the activity while the *class level* provides rich information from beginning to end of the activity (Table 6-4, column Min 10). Our analysis indicates that teachers could identify the major groups anomalies based on the *class level* and confirm them after looking at the *detailed group level*. Visualisations were understood by teachers (96% of correct answers in post-study questionnaires) and helped them divide their attention effectively according to group's needs. Quantitative data does not provide details of group's collaboration but it provided information for teachers to infer whether groups were potentially engaged in non-collaborative activity.

### 6.4.7. Section Summary

The goal of the study described in this section is to present *real-time* data from interactive tabletops, combined with data mining results, in an interactive dashboard that helps teachers monitor group activities at a multi-tabletop learning environment. The section presented the design and evaluation of the teacher dashboard that shows information at two levels: a class summary and a detailed group timeline. **Evaluation results indicated that the dashboard allowed teachers to effectively detect which groups encountered problems in terms of collaboration.** The *class level* of the dashboard provided information from the beginning of the activity and was used as a decision making tool to help teachers manage their attention and interventions. The *detailed group level* shows chronological information that was considered effective for assessing task progress after class. The evaluation was limited to pre-recorded data for the purpose of repeatability.

## 6.5. Chapter summary

This chapter presented two main studies focused on providing the teacher with key visual indicators of collaboration that can help them recognise group's strategies, behaviours and possible problems. These visualisations are limited just to mirroring quantitative information that can be easily processed through our unobtrusive capture environment (COLLAID) but that can be hard for the teacher to see, especially when she needs to attend to multiple groups.

To achieve this, and assess the design of our sets of visual representations of group's interactions, we conducted two studies. The first study sought to design and evaluate the effectiveness of an initial set of visualisations to inform teachers about different aspects of group's collaboration and progress on their task. The second study included the implementation of a second set of visualisations, grounding on the former; the design of a teacher's dashboard and the evaluation of its effectiveness to 1) drive teacher's attention and interventions at a small group classroom activity; 2) show detailed and distilled information about the progress of specific groups that can be revised if the teacher suspects that the group may present problems in their performance or collaborative interactions.

Results of these studies serve as a foundation for the design of key visual indicators of collaboration that can be useful for the teachers. Even though the learning task in both studies involved the concept mapping activity, most of the visualisations contained in the dashboard can be generalised to other domains where egalitarian participation is desirable. We list the lessons learnt in this chapter.

1. *Quantitative information from multiple sources can provide with key information to teachers about small group's collaboration.* The think-aloud technique used in the studies showed that teachers simultaneously use information obtained from more than one visualisation in order to triangulate evidence and generate their own hypotheses about the level of collaboration or learning behaviour of a group.
2. *Quantitative information is particularly useful to drive a teacher's attention when they need to attend multiple groups.* Most of the visualisations implemented in the two last studies provide simple quantitative information. Even though these visualisations neglect much of the

quality of the student's products or the content of their verbal interactions, the studies proved that they can alert teachers and enable them to decide which groups most need support. This is particularly important in learning scenarios where teachers need to divide their attention and limited time among multiple small groups.

3. *Teachers require minimal information, especially when monitoring multiple groups.* There are a variety of options to visualise student's data. Specifically, the third study showed that teachers have different information requirements according to the context of the learning activity. This means that teachers need succinct and distilled information while orchestrating multiple groups in the classroom. This complies with the principle of minimalism in *classroom orchestration* (Dillenbourg et al., 2011). By contrast, more detailed information can help the teacher to understand aspects of the process followed by particular groups of students. This is useful when the teacher is not in front of the group, for example for post-class analysis when the teacher can access to group indicators, such as the ones presented in the first study.

4. *Teachers are less likely to trust processed information.* Results of data mining algorithms or models do not necessarily show *how* resulting indicators are calculated. In the third study we presented the teacher with an indicator of "collaboration" or symmetry. However, it does not show all the features and the decision tree used to obtain the level of "collaboration". The general agreement of teachers was that they prefer to make sense to the information provided themselves (in this case, from student's interaction and participation data) rather than getting a global indicator of performance. Refer to Table 6-4.

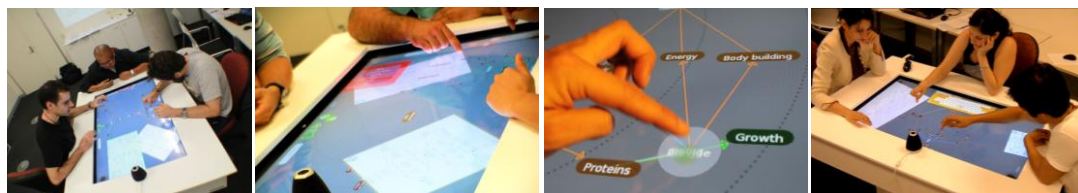
This chapter presented three small-scale studies that aimed to display key student's indicators and design tools that can help teachers and researchers to better understand collaborative learning at the tabletop. These also serve as a basis to improve the design of a learning environment to be used in larger scale studies or real educational settings. The next two chapters present such larger studies. Chapter 7 presents a complete study, conducted under controlled conditions, which offers the opportunity of performing deeper analysis of student's data. Chapter 8 presents two large studies conducted in authentic classrooms.



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## Chapter 7: Data Analytics of Collaboration in a Single-Tabletop Environment

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*"Most great learning happens in groups.  
Collaboration is the stuff of growth"*  
-Sir. Ken Robinson

**Summary:** This chapter presents an approach to exploit the potential of our enhanced tabletop to discover and make visible key patterns of collaboration from student's data. We describe a larger study conducted in a single-tabletop learning environment with university students using concept maps to represent their understanding. We use our learning environment to automatically capture student's interaction data and then analyse those by using data mining, learner modelling and statistical techniques. This analysis can help discover patterns of interaction and understand the strategies that are associated with cases where small group of students either successfully collaborate or face problems. Overall, this chapter describes i) our novel experimental setting in which a series of learning activities are scripted to allow students to build artefacts, both individually and collaboratively; and ii) a deep data analysis of student's collaborative interactions based on a set of data sources, including: application logs, detected speech, observations, tests and the produced artefacts.<sup>1</sup>

### 7.1. Introduction

Previous chapters have established the ground for a larger study of student's interactions around a multi-touch tabletop. Chapter 4 presented three studies that showed both the feasibility and of the requirements for the design of an effective face-to-face learning setting that can capture and analyse key student's data in order to discover interaction patterns. Chapter 5 described the design of COLLAID, our *sensing system* that extends a regular tabletop device to capture student's face-to-face data, and CMATE, our concept mapping tool. Then, in Chapter 6, we used CMATE in a second set of three small scale studies that investigated the effectiveness of visual indicators of collaboration to enhance teacher's awareness. This chapter draws upon all these studies. Interactive tabletops can be used to provide new ways to capture traces of face-to-face collaborative learning. This little explored and somewhat hidden potential of these devices can be exploited to enhance teachers' awareness of students' progress based on interesting patterns from the captured traces of interaction. These student's data can make key aspects of collaboration visible and highlight possible problems.

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<sup>1</sup> Parts of this chapter have been published in international conference proceedings of CMC2012 (Martinez-Maldonado et al., 2012c); and in the International Journal of Computer-Supported Collaborative Learning ijCSCL (Martinez-Maldonado et al., 2013b).

This chapter demonstrates that it is possible to automatically discover patterns of interaction that can help teachers, researchers or designers make visible some collaboration strategies followed by students. Figure 7-1 shows the goals, contributions and validation methods addressed in this chapter, particularly for the goal presented in Section 1.3: **providing tools to enhance awareness about student's collaboration in a single-tabletop learning setting and under ideal conditions.**

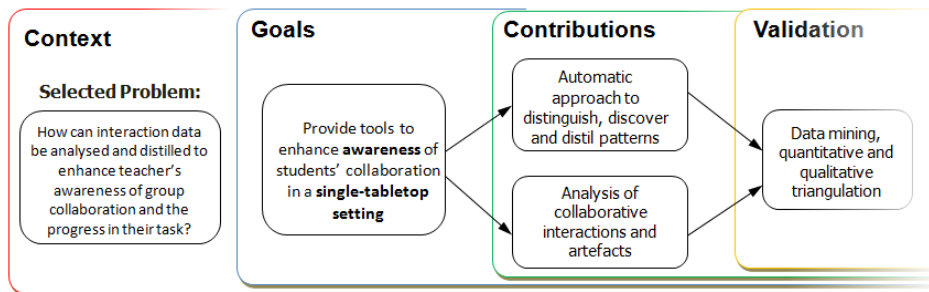


Figure 7-1 Context, goals, contributions and validation of Chapter 7.

To achieve this goal, we conducted a larger study based on a well-defined face-to-face collaborative learning situation: *a small group sharing and challenging their individual perspectives at an enhanced interactive tabletop* (refer to Figure 7-2). This study provides evidence that the implementation of our conceptual framework and technological setup can be applied to address key questions of collaborative learning.

We validate the instantiation the TSCL-Conceptual Framework (see Chapter 3) in a single-tabletop learning setting by developing two different approaches to analyse student's interactions:

1. an automatic approach to *distinguish* groups according to their level of collaboration, *discover* key patterns of interactions and *distil* these in order to associate them with higher level group strategies (**focused on student's actions**); and
2. an approach to *analyse* group activity mainly based on *measures of the group artefacts*, in the form of concept maps (**focused on student's learning products**).



Figure 7-2 A small group sharing and challenging their individual perspectives at our enhanced tabletop.

In terms of the TSCL-Conceptual Framework, this chapter is about the Data Analytics Foundation (DAF). We identified the *sources* from which information can be captured in this kind of learning environment. They include: the group as a unit of analysis, individual learner's activity, and the digital artefacts that students produce during the learning task. Figure 7-3 lists the analysis techniques and group indicators that we applied to the data captured from these sources. Some group indicators that were explored in previous chapters are fundamental in the design of the data analytics approach to be described in Section 7.3. These include indicators of the extent and equality

of student's participation, interweaving of logs of speech and touch, progress of the task, parallelism, concurrency, levels of collaboration and analysis of artefacts. For the analysis of collaboration we use simple techniques such as similarity measures, descriptive statistics, analysis of correlation and significance. Additionally, we apply three data mining techniques: classification, clustering and sequence mining algorithms.

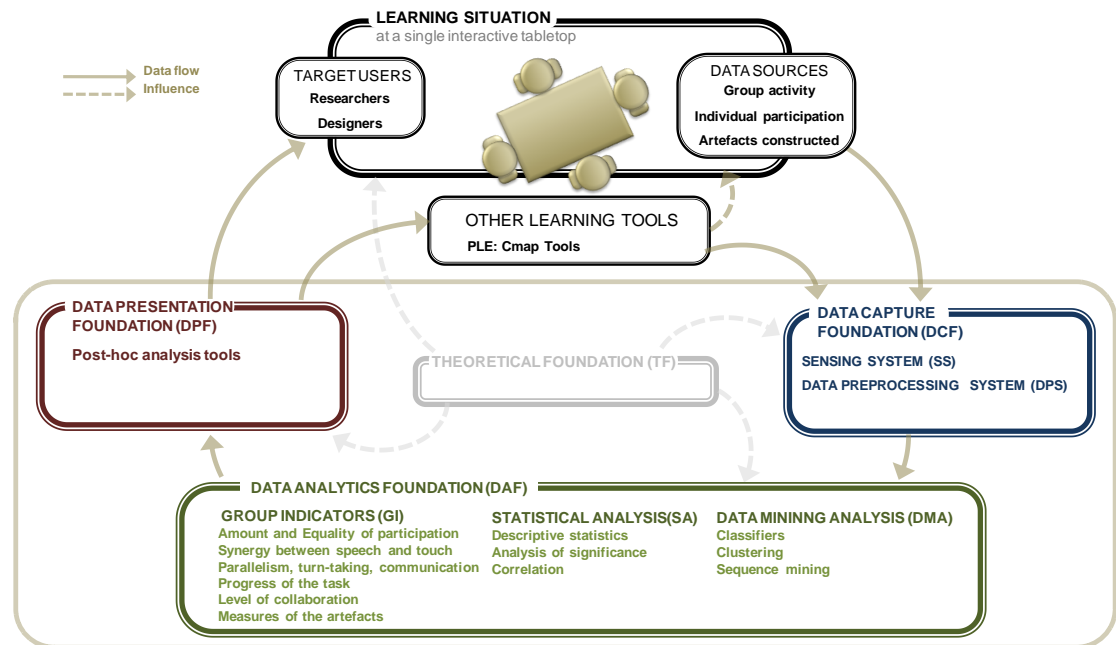


Figure 7-3 Larger-scale study in context with the TSCL-CF.

The chapter is organised as follows. Section 7.2 describes the study design, the context of the learning activity and details about the student's tasks. Section 7.3 presents the automatic approach to distinguish, discover and distil patterns of interaction using data mining techniques. This part of the analysis is mostly focused on student's actions. Section 7.4 presents a set of hypotheses regarding the analysis of the artefacts that students built during their learning experience. This second analysis is mostly focused on student's learning products.

## 7.2. Larger-Scale Study Design: study in the lab

This section describes the design of a study to assess whether the data captured in a tabletop learning environment can provide useful information about learner collaboration. This includes the description of the methodology and the concept mapping application used.

### 7.2.1. Study Design and Participants

One approach that has proved successful to foster meaningful learning is to follow the construction of individual concept maps with a collaborative phase (Engelmann and Hesse, 2010; Novak, 1995). This gives students the opportunity to first think about their personal understanding and then focus on establishing common ground with others, negotiating meanings and generating group knowledge (Tifi and Lombardi, 2008). Sixty students mostly enrolled in science subjects were recruited to participate in the study. An initial focus question was posed to the students: What types of food should we eat to have a balanced diet? Their goal was to create concept maps after studying the Australian Dietary Guidelines 2011 published by the National Health and Medical Research Council of Australia. Participants were organised in triads, mainly grouped so they knew each other.

Before the activity, students received instruction on concept mapping and were requested to draw a training concept map not related to the nutrition domain. Then, they were asked to read a one-page article based on the dietary guidelines and draw a concept map individually at a personal

computer using CmapTools (Figure 7-4, 1). After this, each triad was asked to build a concept map at the tabletop (Figure 7-4, 2). This application was loaded with the individual maps previously built, allowing learners to have access to the concepts, linking words and an image of their maps.

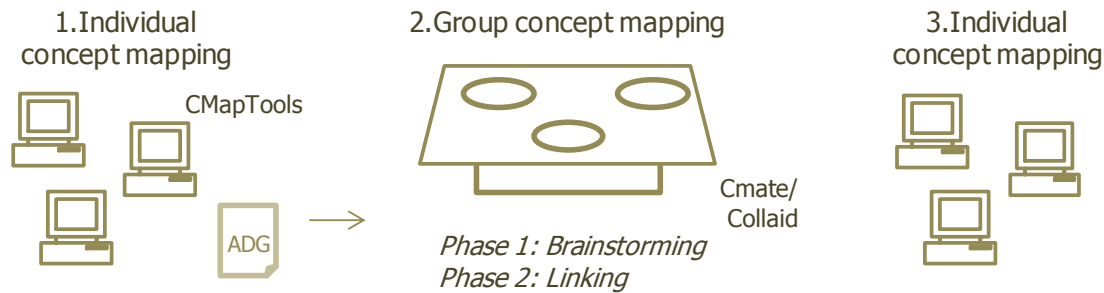


Figure 7-4 Learning setting: 1) concept mapping based on the Australian Dietary Guidelines (ADG); 2) group concept mapping; and 3) individual concept mapping.

The group activity had two phases: i) *brainstorming*, where students were only asked to add the most general concepts for their joint map (they were advised to spend the first 5 to 10 minutes for this); and ii) *linking*, where students could create propositions and add more concepts if needed (20-25 minutes). They had 30 minutes for building individual maps and 30 minutes or more for the collaborative step. Finally, each learner was asked to draw an individual map again (Figure 7-4, 3). An example final group concept map built using CMATE is shown in Figure 7-5. As discussed in previous chapters (refer to Section 5.3) each element at the tabletop is coloured according to the students who added such an element. In this concept map most of elements were added by one student (see orange/dark-yellow links and concepts).

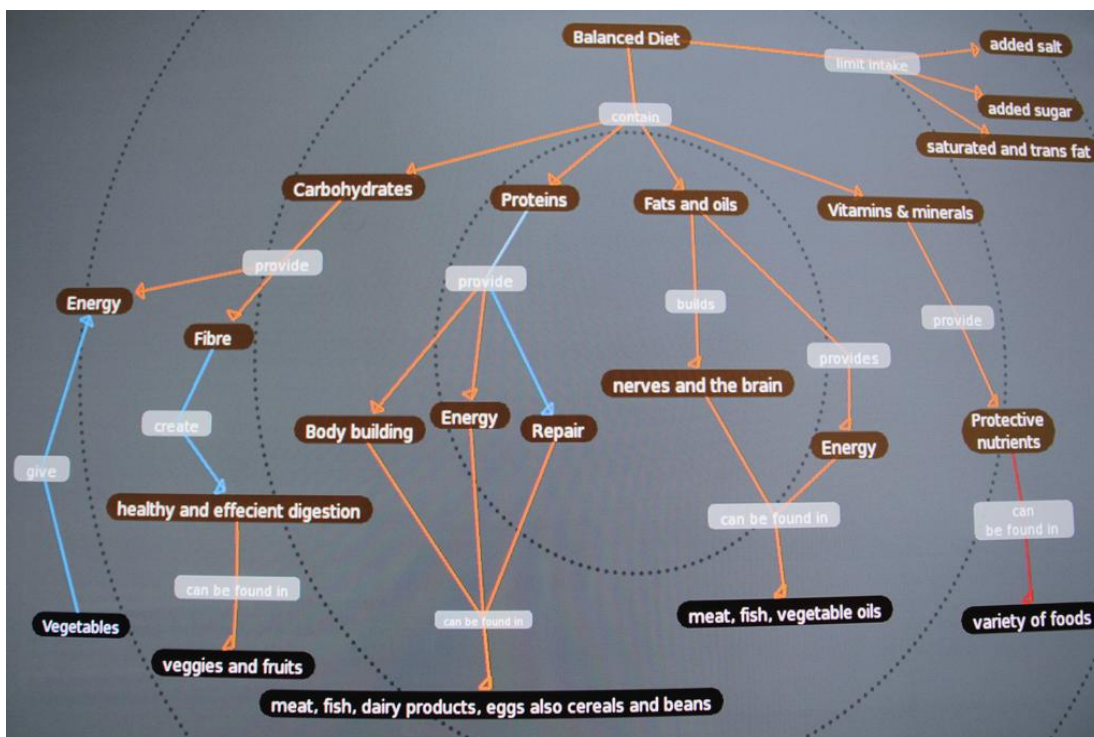


Figure 7-5 An example concept map mainly built oriented towards one of the students. The colours of lines and concepts indicate who created each concept or proposition

In this study we make a clear distinction between the brainstorming and linking phases since the learning goals, the duration (5-10 and 20-25 minutes respectively) and the range of students' actions are different for both activities. This is particularly important for the analysis presented in Section 7.3. Therefore, we describe the exploration and analysis of students' data for each separately.

### 7.2.2. Individual Concept Mapping

We consider individual concept maps as graphical representations of student's understanding. Following recommendations from the concept mapping practice (Cañas and Carvalho, 2004), students were free to use their own words to label the concepts and links. They were also free to decide how to structure the elements of their map (e.g. hierarchical, concentric or flowchart arrangements). We provided an initial list of concepts, extracted from the text, to increase the chances of having *comparable* maps. However, students were free to use them, ignore them or create their own concepts and linking words at any time. Figure 7-6 and Figure 7-7 show two individual concept maps created by 2 students from the same group. In these examples we can see how different the student's perspectives can be even when all students have used the same material and started with the same list of suggested concepts.

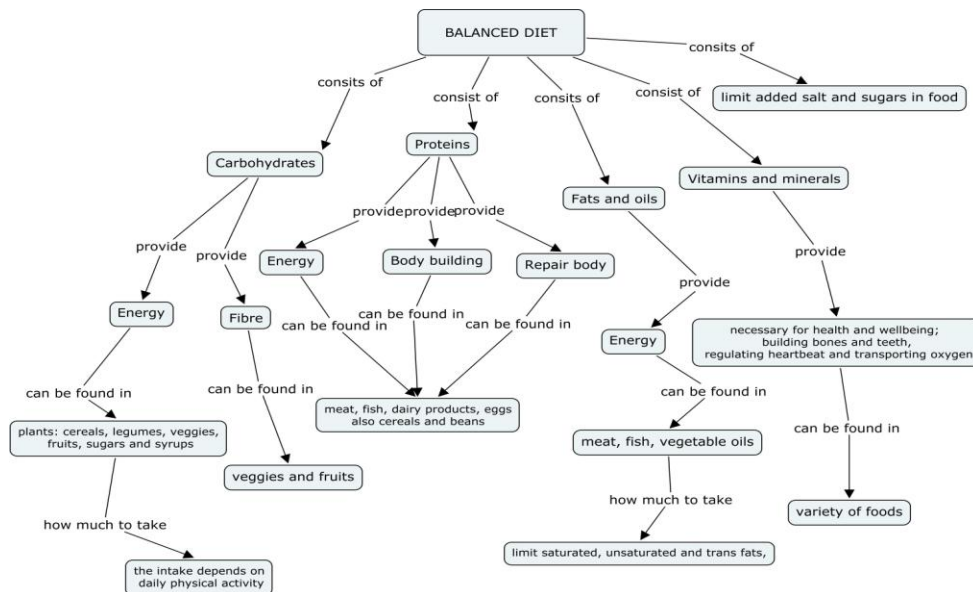


Figure 7-6 Example pre-individual concept maps built by a student of the group who built the concept map shown in Figure 7-5.

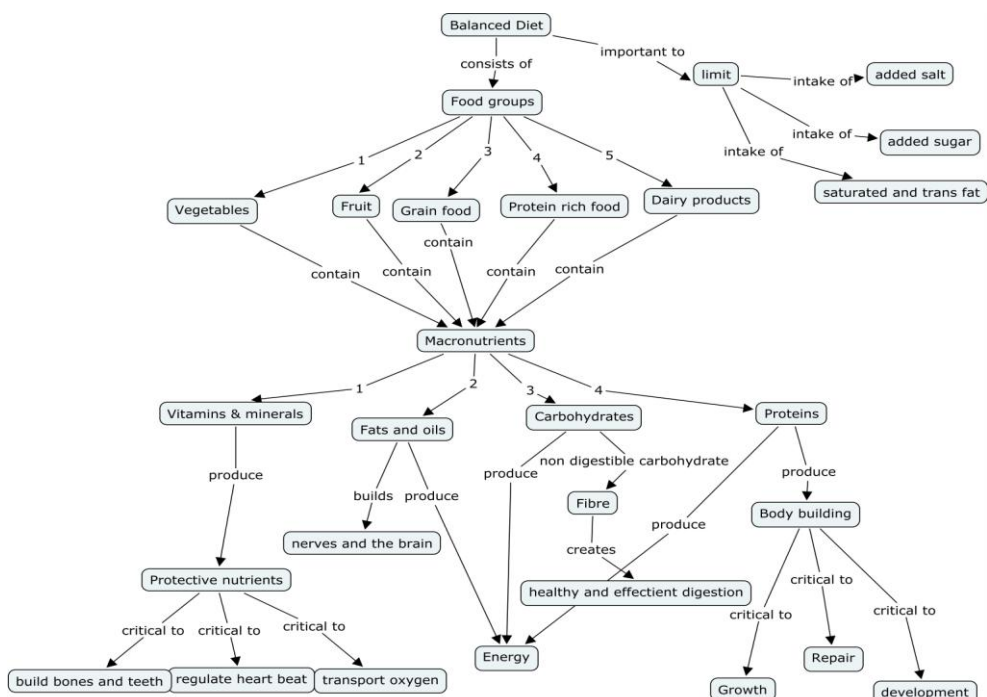


Figure 7-7 Example pre-individual concept maps built by another student of the same group who built the concept map shown in Figure 7-5.



For these examples, the individual concept map shown in Figure 7-7 predominated in the final group map shown in Figure 7-5. In this particular case, the individual map belongs to the student who added most of the elements to the map (orange/yellow student, see coloured elements in Figure 7-5). By contrast, only a few propositions from the map of a second student appear in the group map. The third individual map of the group (not shown) was very different and it was barely considered by other group members during group map building. Other groups behaved differently. Some groups created a totally different group map from the 3 student's individual maps; in others the propositions from most active students did not dominate. These observations motivated the analysis of artefacts discussed in Section 7.4.

### 7.2.3. Collaborative Concept Mapping

As in the studies described in Sections 6.2 and 6.4, COLLAID captured the learner's face-to-face interactions at the augmented interactive tabletop. This allows students to discuss and work on building a joint solution while the enhanced tabletop detects multiple simultaneous touches, recognises which users provided each input by tracking the position of each student around the table and differentiates verbal communication. In this study the full version of CMATE was used.

The tabletop application initially provides each learner with three tools: a list of concepts, an onscreen keyboard for editing phrases, and a resizable representation of their individual concept map. Figure 7-8 shows three different triads working on building a joint map while consulting their individual maps on the tabletop (large white rectangles on the interactive surface in the figures). In all figures, the microphone array, that recognises when each learner is speaking, is located at one side of the tabletop. In the brainstorming phase, the interface only allowed students to add concepts from their lists, create new concepts and open their individual maps. For the linking phase students were allowed to additionally create propositions and use a menu to change the concept map layout.



Figure 7-8 Individual maps opened on the tabletop.

We distinguished between the touch events captured by the tabletop hardware and what we call *meaningful physical actions*, which produce a change in the collaborative artefact. For example, to add a concept, a learner can search for the desired word from their list or decide to create a new concept. For simplification we associated all the touch events with only one higher level action: *adding a concept*. The *meaningful physical actions* are illustrated in Figure 7-9. These are adding, deleting, editing and moving concepts or linking words and accessing individual maps on the tabletop (Figure 7-8). Therefore, other actions, such as interactions with the menus (Figure 7-9, top-left and right) or specific corrections while typing new words (Figure 7-9, bottom-right), are considered at a lower level of abstraction and not considered for analysis.

The initial *raw data* for each group initially consists of two long sequences of actions: evidence of *verbal* speech by each learner and low level identified *physical* actions (including those that do not make a direct change on the learning product). These raw data are transformed into a list of *meaningful actions* and *verbal utterances*, which are defined as: *item-action* = {Action, Resource, Author, Owner, Time, Duration}, where Action can be: *Add* (create a concept or link), *Rem* (delete), *Mov* (move), *Chg* (editing a concept or linking word), *Open*, *Close* (individual maps) or *Speech* (for utterances). Resource can be: *Conc* (concept), *Link* (proposition) or *Indmap* (individual map). Author is the identifier of the user who performed the action, Owner is the identifier of the user who created or owned the Resource, Time is the time when the event occurred and Duration is the time taken to complete the action (for utterances). Multiple touches to perform a single action and interaction with menus were not considered. The original filtered sequence obtained for each group contained from 434 to 1467 *meaningful physical actions* and from 83 to 627 *utterances*.

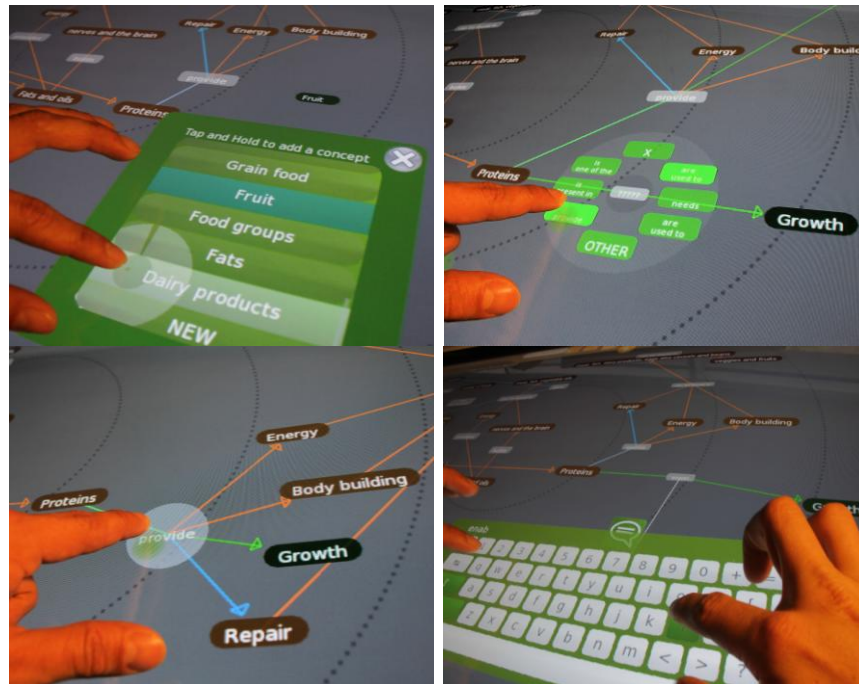


Figure 7-9 Meaningful physical actions. Top-left: Personal list of concepts used in the individual stage loaded to the tabletop. Top-right: List of suggested linking words available when a student creates a new link at the tabletop (e.g. Proteins – provide – growth). Bottom-left: All elements can be moved by direct touch and links can be merged to organise the concept map. Bottom-right: Students can add new concepts and linking words at any time or edit the links (e.g. for the same link change the word “provide” to “enable”).

The shape of the interactive tabletops is rectangular (same dimensions as in the previous studies described in Chapters 4-6). This offers similar opportunities of participation but with different degrees of limitation. The students seated at the short edges of the tabletop evidently cannot reach certain objects that are on the opposite side of the tabletop. As the focus of our work is not on studying territoriality, we designed the study using two different arrangements of students.

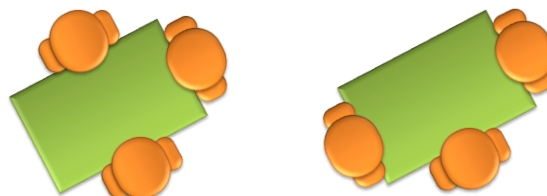


Figure 7-10 Position of learners around the tabletop.

These allow verifying that there is no correlation between higher level behaviours in students (such as dominance, free-riding or collaboration) and their seating positions. Half of the triads in this study was arranged each according to one of the physical dispositions of users depicted in Figure

7-10. We did not find any correlation between the seating position and the level of collaboration of the groups or the amount of verbal/physical participation of individual learners.

#### 7.2.4. Quantitative Assessment of Quality of Collaboration

The small scale study presented in Section 6.2 demonstrated that individual students within a small group working around the interactive tabletop may behave in quite different ways. The ideal situation is that all students work together and collaborate showing a coordinated group effort. However, we found that some students tend to dominate, not allowing other group members to participate in formulating a joint solution. By contrast, some students may step back and stop contributing to the group.

Acknowledged this, all 20 sessions were assessed quantitatively. The goal of this analysis was to differentiate the groups in terms of whether the quality of their collaboration was high or low. We applied the analysis method designed by Meier et al. (2007) which defines nine qualitative dimensions of collaboration that are rated quantitatively. These dimensions are: mutual understanding (which assesses grounding processes), dialogue management (which assesses turn taking and coordination of the communication process), information pooling (which assesses elicitation of information and giving appropriate explanations), consensus reaching (which assesses discussion to reach a joint decision), task division (which assesses how well students manage tasks dependencies), time management (which assesses how students deal with time constraints), technical coordination (which assesses how students deal with technical interdependencies), reciprocal interaction (which assesses social interactions and equality in contribution), and individual task orientation (which assesses students' motivation). Further details about the assessment should be consulted directly in Meier et al's (2007) rating handbook.

The first 8 dimensions are group assessments and the last includes individual assessments per student (therefore, there were 3 assessments for task orientation). Each dimension is quantified as a whole number ranging from -2 (very bad) to 2 (very good). We aggregated these scores to obtain a single score. An aggregated score below zero was considered as *less collaborative* (or low collaboration) and positive scores as *more collaborative* (or high collaboration). This gave 10 groups with negative scores (-10 to 0). The other 10 groups had scores from 5 to 19. The averages were -4 (SD=3) (low collaboration) and 13 (SD=5) (more collaborative), where these differ by at least twice the standard deviation in each case. Two different raters tagged the sessions following the same rubrics as (Meier et al., 2007). Inter-rater reliability was high – Cohen's  $k = 0.80$ . This qualitative rating scheme was useful to generate a quantitative measure to distinguish the groups. However, it still has the limitation of requiring human judgement.

#### 7.2.5. Section Summary

**This section described the design of the study presented in this chapter.** The goal is to allow learners to make a concept map that represents their collective understanding and, at the same time, unobtrusively capture their interactions with the system and with the other learners. At the tabletop students can decide if they work from their individual work or build a totally new group concept map. They can also decide if they work collaboratively, how they divide the work, how they manage their time or if one student completes the entire task. The design implies that there is no intervention on the collaborative process, by either the system or external agents (such as the researcher or designer). The system captures student's information using the sensing systems.

### 7.3. Mining Traces of Student's Activity

This section describes the *design* of an automatic approach to *distinguish*, *discover* and *distil* patterns of interaction to associate them with higher level group's strategies based on three data mining



techniques<sup>1</sup>: a classification model to detect periods of collaboration; sequential pattern mining to find sequences that differentiate groups; and clustering to group similar patterns and associate them with higher level strategies. We also present an *instantiation* of the approach applied to our 20 triads of students. The main contribution of this section is an approach to automatically discover salient common patterns of verbal interactions between peers and touch actions on the shared device, which can be associated with strategies that distinguish high from low collaboration groups.

### 7.3.1. Research Questions

We identified six research questions that link the observable patterns or strategies that offer promising in differentiating groups according to the *extent* of their collaboration. First, our previous studies suggested that it is possible to measure the level of collaboration in a collocated setting (Section 4.2) with acceptable degree of accuracy and that the model can be simplified and applied to tabletop environments. The first goal is to investigate if that model can be generalised and applied to this larger dataset. Therefore, the first question is:

1. Can we automatically detect the occurrence of collaboration using quantitative measures of student's interactions at the tabletop?

Second, previous research on collaboration around interactive and non-interactive tabletops suggested that groups that produce *better* solutions have more equality in discussion (Roman et al., 2012). This finding motivated our next two questions; these primarily focus on the exploration of *verbal activity*, and its timing in relation to the *physical tabletop activity*.

2. Can we distinguish more collaborative from less collaborative groups by the interwoven stream of students' *verbal and physical participation*?
3. Can we distinguish more collaborative from less collaborative groups by extracting patterns of interaction based on just students' *verbal participation*?

Other studies inspired our fourth question; these suggested that when a learner interacts with digital artefacts created by other students, this may trigger further discussion that is beneficial for collaboration (Fleck et al., 2009). In the context of collaborative concept mapping, this may be associated with the concept of *transactivity* which is the extent to which one group member refers to, or builds their own ideas upon, their peer's contribution (Molinari et al., 2008; Stahl, 2013). Strictly, this would be measured in terms of the number of links that each learner creates using concepts that other learners added to the group map. Our approach goes a step further by including all the interactions a student performs on others' objects, including moving them. The fourth question is:

4. Can we distinguish more collaborative from less collaborative groups based on patterns involving *traces of interaction of students with others' objects*?

We also explored the strategies followed by different groups to access individual learners' representations of knowledge inspired by the studies on mutual awareness by having access to individual concept maps (Engelmann and Hesse, 2010). The fifth question is:

5. Can we distinguish more collaborative from less collaborative groups in terms of the actions that follow up the access to others' knowledge structures?

Finally, we want to investigate whether it is possible to link patterns of verbal and physical participation with group strategies similarly to the study presented in Section 4.4, a data mining approach to cluster similar sequential patterns to associate them with group's behaviours.

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<sup>1</sup> Parts of this section have been submitted to the International Journal of Computer-Supported Collaborative Learning iJCSCL.

6. Can we group patterns of interaction by interweaving student's *verbal and physical participation and associate them with higher level group strategies?*

### 7.3.2. Preliminary Analysis

Before any pattern mining was undertaken, we explored the data to analyse if, by using simple statistics, it is possible to distinguish groups in terms of their extent of collaboration. First, we looked at the time that each group spent in each phase. Table 7-1 shows the time spent by both more and less collaborative groups to complete the activity. We can observe that more collaborative groups tended to keep to the suggested time for each phase (5-10 and 20-25 minutes respectively). While the less collaborative groups had similar averages, they had higher deviations. Even though the differences are not statistically significant, some of the less collaborative groups spent either less or more than the intended time for both phases. The issue to address is whether quantitative data can provide insights about the strategies that lead these groups to be less collaborative.

Table 7-1 Average time taken by groups to complete each collaborative phase.

	More collaborative	Less collaborative
Phase 1 (brainstorming)	10' ( $\pm 3$ )	10' ( $\pm 7$ )
Phase 2 (linking)	21' ( $\pm 2$ )	24' ( $\pm 9$ )

\*Time in minutes

To further explore the dataset, we draw on our previous work on group visualisations (Section 6.4) and our research questions to focus on three aspects of collaboration at the tabletop: *physical interaction*, *verbal interactions* and the synergy between these two. We analysed the *brainstorming* and *linking* phases separately as the range of actions and learning objectives were different. First, regarding the *physical activity*, we explored the cumulative interaction by each learner with other student's objects through the *graphs of interaction with other's objects*. Figure 7-11 shows three visualisations, where the size of the circles indicates the number of touches by learner. The thickness of the lines linking the circles represents the amount of interaction between pairs of learners, in terms of actions on objects created by the other. The visualisation in Figure 7-11-a corresponds to a group that behaved quite collaboratively on this aspect. It shows three similar sized circles, each linked to the other, with two lines, albeit of various widths. Less collaborative groups on this dimension are illustrated in b and c, with different sized circles and, notably in c just one connection for the green user acting on objects of the yellow user.

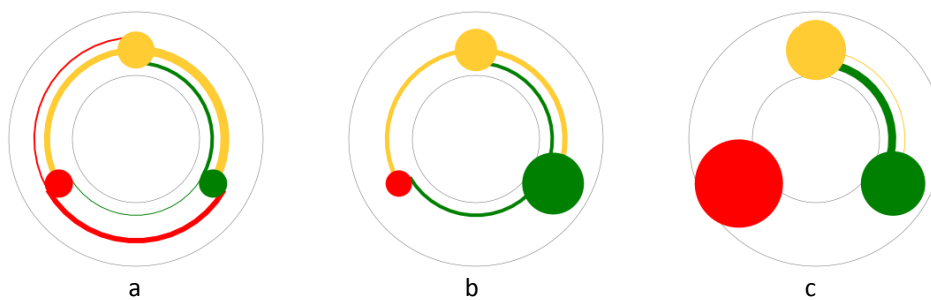


Figure 7-11 Graphs of interactions with other's objects for (a) a collaborative group, (b) a group with a free-rider, and (c) a non-collaborative group (details presented in Section 6.4).

Additionally, it has been found that for tasks like ours that called for equal participation, groups in which learners participate asymmetrically are sometimes associated with cases of social loafing or disengagement (Dillenbourg, 1998). For this, we used the *Gini coefficient* (Harris et al., 2009). Our earlier work found that coefficients close to 0.5 are associated with non-equal activity (Section 4.3). Table 7-2 summarises the amount of physical activity in our triads, the interaction of learner's with other's objects and the symmetry.

In Table 7-2, for the *brainstorming* phase, all groups (both more and less collaborative) had similar levels of physical activity and high symmetry (>300 raw touches, *Gini* coeff. 0.18). The main difference between Phase 1 and 2 was that in the *linking* phase, learners interacted more (and more unequally) with objects created by their peers. Overall, the level of action on others' objects was 29% for high groups and 25 % for low groups (last Column). For the symmetry of physical activity, the high groups, shifted to less symmetric (rising *Gini* coeff. from 0.18 to 0.35) while the low groups were similar, 0.18 to 0.20). In fact, learners in low groups appear to be more equal in their physical activity (Column 2), consistent with the trend reported in (Martinez-Maldonado et al., 2011c). Contrary to what the visualisations of Figure 7-11 suggest, we found that low groups had more signs of symmetry in the physical interaction with other's objects (*Gini* coeff. 0.2 for low and 0.36 for high groups). However, there were no significant differences that could distinguish groups as either more or less collaborative. Overall, these simple analyses provide a rather complex picture that makes it unclear how a group of learners, or their facilitator or teacher, might make use of these measures.

Table 7-2 Average values of physical activity, interaction with other's objects, and symmetry.

	Collaboration	Physical activity (touches)	Physical activity (symmetry)	Touches on others' objects	Touches on others' objects (symmetry)	Touches on others' objects (% all actions)
Phase 1 (brainstorming)	Low	344 ( $\pm 184$ )	0.18 ( $\pm 0.1$ )	39 ( $\pm 54$ )	0.63 ( $\pm 0.3$ )	10 % ( $\pm 10$ )
	High	320 ( $\pm 120$ )	0.18 ( $\pm 0.1$ )	32 ( $\pm 25$ )	0.63 ( $\pm 0.2$ )	9 % ( $\pm 7$ )
Phase 2 (linking)	Low	897 ( $\pm 475$ )	0.20 ( $\pm 0.1$ )	211 ( $\pm 80$ )	0.20 ( $\pm 0.1$ )	25 % ( $\pm 6$ )
	High	740 ( $\pm 120$ )	0.35 ( $\pm 0.1$ )	205 ( $\pm 78$ )	0.36 ( $\pm 0.2$ )	29 % ( $\pm 11$ )

Secondly, we explored simple indicators of speech that might provide hints of possible issues in the group. Table 7-3 shows that the more collaborative groups had higher levels of verbal activity. In Column 1, we see time spent speaking of 457 against 270 in Phase 1 and 773 against 531 for Phase 2. For the number of utterances, in Column 3, there is a similar situation, with 138 against 91 in the brainstorming phase, 229 against 109 in the *linking* phase. Both phases had greater symmetry for the high collaboration groups (Column 2, *Gini* coeff. 0.19 against 0.34, then 0.19 and 0.30 for the linking phase). Even though the large standard deviations affects the analysis of significance, these indicators suggest the potential value of deeper exploration at a lower level of granularity.

Table 7-3 Average values of verbal activity, meaningful physical actions and number of accesses to individual concept maps at the tabletop.

	Collaboration	Audio time (seconds)	Audio time (symmetry)	Utterances	Meaningful physical actions	Access to Individual map
Phase 1 (brainstorming)	Low	270 ( $\pm 297$ )	0.34 ( $\pm 0.19$ )	91 ( $\pm 84$ )	105 ( $\pm 65$ )	4 ( $\pm 4$ )
	High	457 ( $\pm 286$ )	0.19 ( $\pm 0.20$ )	138 ( $\pm 86$ )	114 ( $\pm 53$ )	7 ( $\pm 5$ )
Phase 2 (linking)	Low	531 ( $\pm 519$ )	0.30 ( $\pm 0.13$ )	109 ( $\pm 176$ )	407 ( $\pm 227$ )	7 ( $\pm 7$ )
	High	773 ( $\pm 366$ )	0.19 ( $\pm 0.07$ )	229 ( $\pm 106$ )	286 ( $\pm 50$ )	8 ( $\pm 3$ )

Meaningful physical actions= Actions that made an impact on the collaborative artefact only.

Additionally, Table 7-3 also shows the average values for what we call *meaningful physical actions*, which affect the size, shape or content of the group artefact. We observed no difference between low and high collaborators in the number of these actions for the *brainstorming* phase (114 and 105 actions respectively) but some difference in the *linking* phase, where the less collaborative groups had more of these actions. Lastly, we count the number of times group members accessed their *individual maps*. The main difference was that the more collaborative groups *always* accessed their maps, while *some* of the low groups never opened a concept map (column 5, *Access to Individual map*, deviations are equal to the average).

We additionally explored the *relationship between verbal and physical actions*. Our previous work (Section 4.3) suggested that the more collaborative groups the higher the levels of symmetric

speech and the lower the levels of physical actions. This can be represented through the *Mixed radars of verbal and physical participation* that model the amount and symmetry of physical and verbal participation. The triangles in Figure 7-11 depict the number of touches and amount of speech by learner (red and blue respectively). Each small circle represents a student. The closer the corner of the triangle is to a circle, the more that student was participating. An equilateral triangle means that learners participated equally. Figure 7-11 shows the representations of three groups. Visualisation *a* shows a collaborative group in which the 3 learners participated quite equally on both dimensions. Visualisation *b* shows a disengaged learner from the activity (left lower red circle); and visualisation *c* shows a learner who had a high level of physical activity but little verbal participation (also left lower red circle).

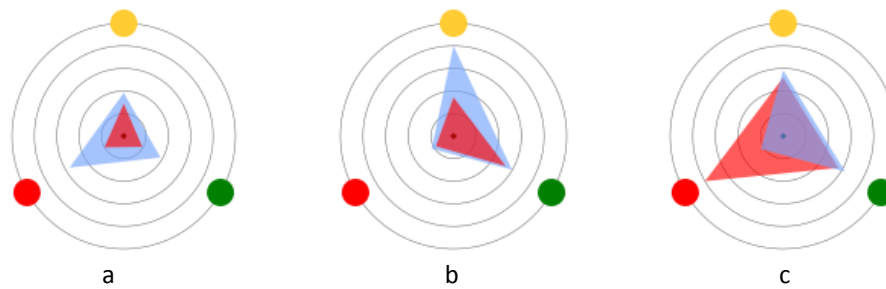


Figure 7-12 Mixed radars of verbal (blue/light triangle) and physical (red/dark triangle) participation for (a) a collaborative group, (b) a group with a free-rider, and (c) a non-collaborative group (details in Section 6.4).

Table 7-4 presents the analysis of the *physical actions* and how these were associated with verbal activity. First, we observed a weak trend in the less collaborative groups performing more physical actions without speech (Column 2, 20% and 75% of all actions for low compared with 13% and 64% for the high groups). By contrast, for actions accompanied by speech, we found that in all groups, individual learners tended not to talk while performing physical actions (Columns 3 and 4). For the *brainstorming* phase just the 16% of such actions were performed in high groups and 14% in low groups. For the *linking* phase this proportion was even lower (below 10%). For the case of physical actions where the speech was from another learner, we found a different situation. An average of 44% of the actions by the more collaboratively groups were performed while other students were speaking (29% of actions for low groups). For the *linking* phase this difference was smaller but still with some difference (25% and 17% respectively).

Table 7-4 Average values of physical actions with no speech in parallel; and physical actions with speech in parallel from the same student and other students.

Collaboration		Actions with no speech	Actions with no speech (% all actions)	Actions with speech by the same author	Actions with speech by same author (% all actions)	Actions with speech by other author	Actions with speech by other Author (% all actions)
Phase 1 (brainstorming)	Low	76 ( $\pm 61$ )	20 % ( $\pm 8$ )	14 ( $\pm 13$ )	14 % ( $\pm 9$ )	29 ( $\pm 22$ )	29 % ( $\pm 16$ )
	High	52 ( $\pm 44$ )	13 % ( $\pm 12$ )	16 ( $\pm 12$ )	16 % ( $\pm 9$ )	45 ( $\pm 35$ )	44 % ( $\pm 20$ )
Phase 2 (linking)	Low	307 ( $\pm 234$ )	75 % ( $\pm 23$ )	29 ( $\pm 28$ )	8 % ( $\pm 7$ )	70 ( $\pm 64$ )	17 % ( $\pm 16$ )
	High	185 ( $\pm 73$ )	64 % ( $\pm 20$ )	29 ( $\pm 28$ )	10 % ( $\pm 6$ )	77 ( $\pm 39$ )	25 % ( $\pm 15$ )

Physical actions= Actions that made an impact on the collaborative artefact only.

Overall, for the measures of activity presented above, each considered in isolation at the end of the activity, were not indicators of significant difference between groups that worked either more or less collaboratively. These averaged values do not take account of additional fine grain information that can be exploited, like the order, authorship or the balance between verbal and physical actions. This suggests the need to integrate contextual information and multiple sources of information simultaneously. Next, we present our approach that includes such contextual information with the sequence of learners actions in order to explore patterns that can help to differentiate groups.

### 7.3.3. Approach

In this sub-section we describe our approach to:

1. *distinguish* which groups of students show high or low levels of collaboration (research question 1 – Section 7.3.4);
2. *discover* frequent patterns of verbal and touch activity that differentiate these groups (research questions 2-5 - Section 7.3.5); and
3. *distil* these patterns of interaction to associate them with group's strategies (research question 6 – Section 7.3.6).

Our approach requires the capture of verbal and touch interactions followed by data analysis based on three data mining techniques. First, a classification model detects periods of collaboration within each small group to generate two datasets: highly and weakly collaborative groups. This is essential to automatically obtain group assessments similar to the one described in Section 7.2.4 but without human intervention. Second, a sequential pattern mining technique extracts frequent sequences that differentiate both highly and weakly collaborative groups. Finally, hierarchical clustering is used to group similar patterns to facilitate their interpretation.

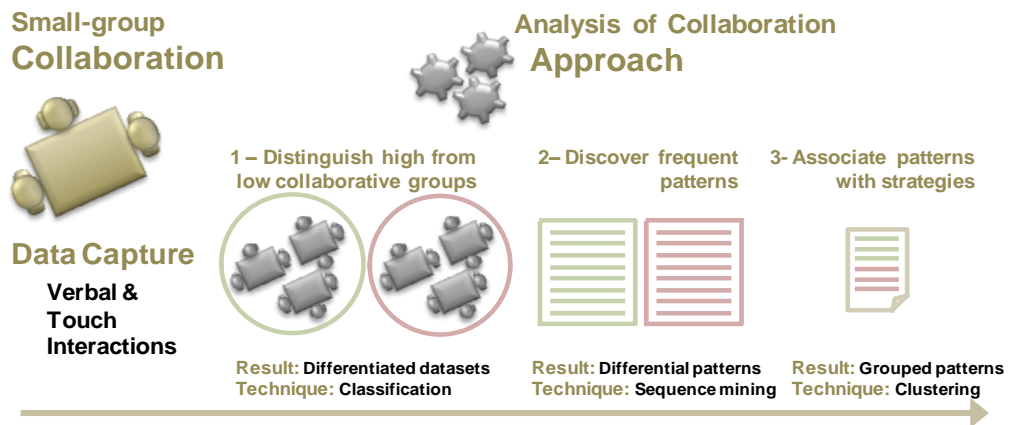


Figure 7-13 Analysis of collaboration approach using three data mining techniques.

### 7.3.4. Distinguishing High from Low Collaboration

This sub-section addresses the Question 1: *Can we automatically detect the occurrence of collaboration using quantitative measures of student's interactions at the tabletop?* To determine the level of collaboration, and distinguish between highly and weakly collaborative groups, we implemented an adapted model produced through the technique presented in Section 4.2.

#### *Pre-processing and Algorithm*

This begins with splitting the total group session into blocks. Then, the Best-First decision tree is used to classify each period of group work according to a set of features of verbal and physical activity. It was implemented as follows:

1. the audio and touch actions of each triad are grouped into *blocks* of period of time  $t$  ( $t=30$  as learnt from the study in Section 4.2);
2. a number of indicators of interaction are calculated per block, including: *total time* of all learner's speech, total number of *utterances*, *symmetry of speech* among the students measured by the Gini coefficient, total number of *touch actions* and *symmetry of these actions*;
3. the algorithm generates a decision tree based on these features to classify each block as matching one of three possible values: *high (H)*, *medium (M)* or *low (L)* collaboration; and,

4. the group is labelled as either highly or weakly collaborative based on the aggregation of all the classified blocks. The result is a dataset divided into *highly and weakly collaborative groups*.

Initially, we tested this method for multi-display settings, where learners have the same opportunities of participation and there are no assigned roles (Section 4.2). It was further extended to multi-touch tabletop systems (Section 4.3). This second study explored a few tabletop sessions and proposed the description of this model in terms of simplified rules. We reported that highly collaborative groups are characterised by high levels of symmetric conversation, fewer physical actions and some asymmetry in touch activity. By contrast, weakly collaborative groups have low levels of talk, asymmetry in the conversation and higher levels of physical activity.

### Results

The classification model presented in Section 4.2 (Study Waterloo 1), and further used for the study presented in Section 6.4 (to design the visualisation called: *Indicator of collaboration*), was applied to each of the half minute blocks of tabletop activity. As a result, 17 out of the 20 (85%) group sessions were correctly identified as either highly or weakly collaborative according to the aggregation of their classified periods (around 60-70 periods in each group).

Table 7-5 Average number of classified blocks for highly and weakly collaborative groups.

Proportion of collaborative blocks			
Collaboration	High	Medium	Low
High	30 ±10	17±6	12±4
Low	8±4	35±8	29±10

Table 7-5 presents the distribution of blocks according to group's collaboration. We can observe an increasing trend to highly collaborative periods in the highly collaborative groups (30, 17 and 12 blocks classified as high, medium and low collaboration). Weakly collaborative groups presented more medium than low collaboration periods, but very few highly collaborative periods (H=8, M=35, L= 29). Some of the indicators of *quality of collaboration* are not easy to determine even through human judgment, and in consequence are more challenging to measure automatically. These results show that it is possible to obtain a modest approximation to detect overall level of collaboration by using simple rules considering only quantitative indicators.

### 7.3.5. Discovering Frequent Patterns.

One of the data mining techniques that has been used to identify patterns that differentiate high from low achieving groups/students is sequence pattern mining. We implemented this technique as it considers the order of the events in contrast to the accumulated statistical analysis of the previous section. For example, Perera et. al. (2009) modelled key aspects of teamwork for groups working with an online project management system by proposing *alphabets* to represent sequential events that can distinguish strong from weak groups. Our own work presented in Section 4.4 proposed a semi-supervised approach to extract sequential patterns of student's activity at a pen-based tabletop and cluster similar patterns to link them with group strategies. Kinnebrew et al. (2012) presented the *differential sequence mining* method (DSM) which automatically compares patterns that characterise high and low-achieving learners including contextual information of student's actions. We implemented a mixed technique by using the DSM algorithm and designing our own alphabet that considers verbal and touch actions performed by multiple students.

#### *Pre-processing: filtering and alphabets*

Even though the content of each *item-action* in its raw format may appear simple (*item-action* = {ActionType, Resource, Author, Owner, Time, Duration}), the complexity of these data is actually high. Each student's action is associated with rich contextual information obtained by interlacing the three sources of information: student's physical actions on the tabletop application, the identified speech participation and the status of the artefact.

The enhanced tabletop can capture not just the students' actions, but it can also link these to whether students were talking whilst interacting with the interface or just talking without touching the table. Furthermore, in terms of the group artefact, student actions can have an impact on the knowledge represented in the concept map or their actions may just modify surface aspects of it. However, not all this contextual data is relevant to the research questions. In fact, if all this rich contextual information is taken into account when extracting patterns, the information would be too detailed to find *meaningful trends* in the interaction.

For example, whilst the authorship of learners' actions seems likely to be important, the exact detail of who is doing what is not necessarily relevant: if the intention is to detect how often students take turns versus a single student performing a sequence of actions, we only need to know whether actions were performed by the same student or by different students. Suppose that in one group, there is a sequence of actions (A, A, B) performed by two students in the following order: student1-A, student2-A, student1-B. In a second group, a similar sequence occurs but the authorship is different: student 3-A, student1-A, student3-B.

Our encoding system must recognise this pattern, regardless of which pairs of the students among 1, 2 and 3 are involved. Consider a second example, for the verbal participation. In one group, two students may perform the following sequence: student1-A and then student2-B. In parallel, a third student may be speaking: student3-utterance for 5 seconds. In this case, it is important to encode the sequence of events in a way that captures parallelism (e.g. speech and touch at the same time).

We therefore designed several alphabets, to encode the raw item-actions at the level of abstraction needed for each research question, so that relevant patterns might be discovered. Next, we describe the design of a number of alphabets to encode student actions into item-actions that capture required contextual information.

#### *Alphabets to encode actions and contextual information*

Inspired by previous work on design of alphabets to mine group behaviours (Perera et al., 2009) and the suffix nomenclature proposed in (Kinnebrew et al., 2012), we designed four alphabets. Each alphabet is associated with a research question in order to investigate the relationship between physical actions, presence of speech, verbal responses, parallelism, ownership, turn taking and access to individual maps. We encode each action using the alphabets in Table 7-6. The coding for an action has *one keyword from each level*. The first two levels correspond to *Resource* and *ActionType*. Levels 3 and 4 add contextual information. We perform three steps to apply the four alphabets:

- i) All *actions* that can be performed on the *resources* are coded with two *keywords*, from Levels 1 and 2;
- ii) All the utterances that did not happen in parallel with any touch actions are coded in the same sequence, with 2 keywords: *Speech* and - *Shrt* or *Full* for utterances shorter or longer than  $u$  seconds respectively ( $u=2$ ).
- iii) The keywords from Levels 3 and 4 are added to each action or utterance. These are different for each alphabet.

Next, we present a detailed description of each alphabet focusing on the specific keywords that are added in the third encoding step.

**Alphabet 1 seeks to address question 2 by exploring the interweaving of verbal and physical participation traces.** First, it focuses on adding the contextual information about the *speech that occurs in parallel with physical actions* (Alphabet 1, Level 3). This includes the keywords: *Sauthor*, which represents that the learner was talking while performing an action; *Sother*, which means that another learner was speaking while the author was performing the action; and *NoSpeech*, which means that when the action was performed no learner spoke.



Alphabet 1 also considers the time, order and author of each action to explore if only one student was building the solution or if their work was more reciprocal (by working either concurrently or completely in parallel). This is represented by the keywords in Level 4, which include: *Tsame*, which means that the previous action was performed by the same author; *Tother*, when the previous action was performed by a different learner (consecutive actions with the keyword *Tother* may indicate *concurrent* work); and *Tparallel*, when the previous action was performed by a different learner less than one second earlier, which is about the time for users to perceive immediateness (Nielsen, 1993). Multiple and consecutive *Move* actions by the same learner were compressed aggregating the keyword *Mult*.

Table 7-6 Four alphabets. 1) Physical/verbal participation; 2) verbal participation; 3) physical action on other's objects; and 4) access to individual maps.

Alphabet 1: Physical-Verbal participation				Alphabet 2: Verbal participation			
Level 1	Level 2	Level 3	Level 4	Level 1	Level 2	Level 3	
Link	<sup>LC</sup> Add / Rem / Chg	NoSpeech	<b>Tsame</b>	Link	<sup>LC</sup> Add / Rem / Chg	<b>NoSpeech</b>	
Conc	Mov / Mult	Sauthor	<b>Tother</b>	Conc	Mov / Mult	<b>Sauthor</b>	
Indmap	<sup>I</sup> Open / Close	Sother	<b>Tparallel</b>	Indmap	<sup>I</sup> Open / Close	<b>Sother</b>	
Speech	Shrt / Full			Speech	Shrt / Full	<b>Start</b>	
				<b>Resp</b>			
				<b>Assen</b>			
Alphabet 3: Touches on others' objects				Alphabet 4: Access to individual maps			
Level 1	Level 2	Level 3	Level 4	Level 1	Level 2	Level 3	Level 4
Obj	<sup>LC</sup> Add / Rem / Chg	NoSpeech	<b>Owner</b>	Link	<sup>LC</sup> Add / Rem / Chg	NoSpeech	<b><sup>I</sup>Pers / NoPers</b>
	Mov / Mult	Sauthor	<b>Difowner</b>	Conc	Mov / Mult	Sauthor	
	<sup>I</sup> Open / Close	Sother		<b>Indmap</b>	<b><sup>I</sup>Open / Close</b>	Sother	
				Speech	Shrt / Full	<b>Start</b>	
				<b>Resp</b>			
				<b>Assen</b>			

**Alphabet 2 focuses on the detailed description of the verbal participation in context with the physical actions.** Following the same rationale described above, this alphabet introduces information about the length, order and authorship of verbal utterances where this is no physical actions in parallel. Figure 7-14 shows an example of the encoding of the same actions for Alphabet 2. It introduces three keywords (Table 7-6, Alphabet 2, Level 3). These are: *Start* (e.g. Figure 7-14, item-action 9), when a utterance has no other utterance immediately before it; *Resp* (response), when a utterance immediately follows a previous utterance by another learner (e.g. item-actions 4 and 11); and *Assen* (assenting), for short utterances (1 to 2 seconds long) that occur while another learner speaks (e.g. item-action 10). We used these rules to automatically code all the utterances. We compared this rule-based tagging with a human tagging in 10% of the dataset and we found 76% agreement in identifying learners' verbal responses. The alphabet also has the keywords associated with speech to encode physical actions (NoSpeech, Sauthor and Sother).

**Alphabet 3 captures the interaction of students with others' objects.** This alphabet considers contextual information about the actions that are performed by learners, either on the objects they initially created, or the ones created by others. This uses the keywords *Owner* and *Difowner* respectively (Table 7-6, Alphabet 3, Level 4). The alphabet also keeps the keywords associated with speech to encode physical actions (NoSpeech, Sauthor and Sother), but it does not include independent utterances. To keep the alphabets as simple as possible but, at the same time, to capture the essential aspects of interactivity on others students' objects, this alphabet does not differentiate among types of objects (only 1 keyword *Obj* for Level 1).

**Alphabet 4 targets the research question that explores the influence of the access to knowledge structures** (question 5). This alphabet keeps the keywords associated with speech in Level 3 as in Alphabet 2, and adds information provided by the keywords *Pers* and *Nopers* (Table 7-6, Alphabet 4, level 4). *Pers* is for actions performed on concepts or links that were in a *personal/individual* map while this is being displayed at the tabletop (as in Figure 7-8) or immediately before. *Nopers* corresponds to the rest of the actions on concepts and links, those that are not in any individual map displayed on the tabletop. The objective of this alphabet is to find possible differences in the actions performed *after* learners *Open* their individual maps (*Indmap*).

*The algorithm: differential sequence mining.*

As a result of encoding the groups' actions, according to the four alphabets described above, we obtained four datasets of encoded item-actions with 2 sub-sets of data each. Each sub-set contains 10 long sequences of item-actions for either a high or low collaboration groups. In order to extract patterns of activity we applied the *differential sequence mining* technique (DSM) developed by Kinnebrew et al. (2012), which looks for sequential patterns that differentiate two datasets.

A sequential pattern is a consecutive or non-consecutive ordered sub-set of a sequence of events that is considered frequent when it meets a minimum *support* criteria (Jiang and Hamilton, 2003). For the DSM technique this is called sequence-support (*s-support*) that corresponds to the number of sequences in which the pattern occurs, regardless how frequently it repeats within each sequence. We set the minimum threshold to consider a pattern as frequent if this was present in at least half of the sequences (*s-support*=0.5) following previous work by Kinnebrew et al. (2012).

The algorithm also calculates consecutive and repeated patterns within the dataset of sequences. This is called instance support (*i-support*). We set the maximum error threshold to 1 to allow the matching of patterns with sub-sequences if there was an edit distance of 0 (perfect match) or 1 (one different action in the sub-sequence) between them. This allows a larger number of sequences to be considered as *differential* even if the matching is not perfect. This has proved effective in matching similar sequences of actions in learning environments (Kinnebrew et al., 2012; Martinez-Maldonado et al., 2011f). The output of this algorithm is a list of frequent patterns that meet the minimum support in each dataset and that distinguish more collaborative from less collaborative groups ( $p < 0.1$ ) also following previous work by Kinnebrew et al. (2012). Next, we present the results of running the algorithm for each research question.

## Results

**Question 2: Can we distinguish more collaborative from less collaborative groups by the interwoven stream of students' verbal and physical participation?** After applying the DSM algorithm on Alphabet 1, we selected the patterns whose i-support distinguished high from low groups with a confidence of at least 90% ( $p \leq 0.10$ ) and that were composed of at least 2 item-actions (e.g. {*Conc-Add-Tother-Sother*}>{*Speech-Shrt*}). We obtained 261 differential patterns. Table 7-7 shows the top-4 most differential patterns found in each sub-set for each phase. For the brainstorming phase, the patterns A, B, C, and D are very similar. All are patterns where students added (*Add*) and arranged (*Mov*) concepts without speaking (*NoSpeech*) and with some degree of parallelism and concurrency (*Tparallel* and *Tother* keywords respectively; found in A, B and C). By contrast, the more collaborative groups displayed a different strategy, by interleaving periods of just verbal activity (*Speech*) with physical actions that were accompanied by other students' talk (*Sother* in patterns E, F, G and H).

Table 7-7 Top sequential patterns found using Alphabet 1. Repetitive keywords and descriptions in bold letters.

Top-4 most differential patterns		Description
<b>Brainstorming</b>	Low collab.	A=Con-Mov-Tsame-Mult-NoSpeech > Con-Add-Tparallel-NoSpeech
		B=Con-Add-Tother-NoSpeech > Con-Add-Tother-Sother
		C=Con-Add-Tother-NoSpeech > Con-Add-Tparallel-NoSpeech
		D=Con-Mov-Tsame-Mult-NoSpeech > Con-Mov-Tsame-Mult-NoSpeech > Con-Mov-Tsame-Mult-NoSpeech
	High collab.	E=Speech-Shrt > Con-Add-Tsame-Sother > Con-Mov-Tsame-Sother
		F=Speech-Shrt > Con-Mov-Tsame-Mult-Sother > Con-Mov-Tparallel-Sother
		G=Speech-Full > Speech-Shrt > Con-Mov-Tsame-Sother
		H=Con-Mov-Tsame-Mult-Sother > Con-Mov-Tparallel-Sother
<b>Linking</b>	Low collab.	I=Con-Mov-Tsame-Mult-NoSpeech > Con-Mov-Tparallel-NoSpeech > Link-Mov-Tother-NoSpeech
		J=Speech-Shrt > Con-Mov-Tsame-Mult-NoSpeech > Con-Mov-Tparallel-NoSpeech
		K=Link-Add-Tsame-NoSpeech>Link-Mov-Tsame-NoSpeech> Link-Mov-Tother-NoSpeech
		L=Con-Mov-Tparallel-NoSpeech > Link-Add-Tsame-NoSpeech > Speech-Shrt
	High collab.	M=Con-Mov-Tother-Sother > Link-Mov-Tsame-Sother > Speech-Shrt
		N=Speech-Full > Con-Mov-Tsame-Mult-Sother > Con-Mov-Tparallel-Sother
		O=Speech-Full > Speech-Full > Speech-Full > Con-Mov-Tsame-Mult-NoSpeech
		P=Speech-Shrt > Con-Mov-Tsame-Mult-Sother > Speech-Shrt > Speech-Shrt>Speech-Full>Speech-Shrt>Speech-Shrt>Speech-Shrt

$p \leq 0.05$

To summarise the rest of the patterns found, Table 7-8 shows the frequency of appearance of keywords in patterns that met the differential criteria ( $p \leq 0.1$ ). Confirming the trends suggested by the examples (Table 7-7), for *brainstorming*, the main difference was that high collaboration groups had more patterns in two main classes: ones with speech and no actions in parallel; ones with speech while other students performed actions (*Speech* and *Sother* appeared in 93% and 43% of the frequent sequences for the high collaboration groups against 50% and 18% of the less collaborative groups).

For the *linking* phase, a similar trend continued. The low collaboration groups had an increased presence of parallelism in their actions (*Tparallel*= 36% for low against 3% for high groups) as in the patterns I, K and L. Additionally, more than 65% of the low collaboration groups' actions were not accompanied by speech (*NoSpeech* >60% for low and <10% for high groups). High collaboration groups showed patterns of sequenced speech in the linking phase (patterns O and P).

This alphabet enabled us to discover that learners tend not to talk while touching the tabletop (*Sauthor* keyword is not present in the top patterns of Table 7-7, and in Table 7-8, the second last column (*Sauthor*) has very low occurrence). There is evidence that a strategy followed by the more collaborative groups involved maintaining high levels of both speech levels and turn taking, accompanied by some physical actions, (Table 7-7, pattern P) and keeping parallelism low. By

contrast, the less collaborative groups had higher levels of physical activity with just a few unconnected verbal interventions (see patterns J and L).

Table 7-8 Proportions of keywords in frequent patterns by using Alphabet 1.

	Collaboration	Speech	Tother	Tsame	Tparallel	NoSpeech	Sauthor	Sother
Phase 1 (brainstorming)	Low	50%	<b>50%</b>	25%	18%	<b>62%</b>	0%	18%
	High	<b>93%</b>	10%	39%	16%	7%	5%	<b>43%</b>
Phase 2 (linking)	Low	45%	<b>32%</b>	53%	<b>36%</b>	<b>65%</b>	2%	11%
	High	<b>92%</b>	4%	31%	3%	10%	0%	24%

p-value&lt;=0.1

*Question 3: Can we distinguish more collaborative from less collaborative groups by extracting patterns of interaction based on just students' verbal participation?* Pattern P in Table 7-7 exemplifies the patterns that need deeper exploration analysis (sequenced utterances). Alphabet 2 was designed to provide more information for these verbal patterns. We obtained 225 differential patterns using Alphabet 2. Table 7-9 shows that most of the less collaborative groups' sequences include actions performed on concepts and links with no speech in parallel, both in brainstorming (patterns A to D) and even more frequently in the linking phase (patterns J, K and L). Additionally patterns show that some utterances were not followed by any response (patterns A, C, D and I with keyword Speech-Start).

Table 7-9 Top sequential patterns found using Alphabet 2.

Top-4 most differential patterns		Description
Brainstorming	A= Con-Add-NoSpeech > Con-Add-NoSpeech > Speech-Shrt-Start > Con-Add-NoSpeech	Start utterance, no response, actions <b>with no speech</b>
	B=Con-Mov-NoSpeech > Con-Add-NoSpeech > Con-Add-NoSpeech > Con-Add-NoSpeech > Con-Add-NoSpeech > Con-Add-NoSpeech	Actions <b>with no speech</b>
	C= Con-Add-NoSpeech > Con-Add-NoSpeech > Con-Add-NoSpeech > Speech-Shrt-Start > Con-Add-NoSpeech	Start utterance, no response, actions <b>with no speech</b>
	D= Con-Add-NoSpeech > Speech-Shrt-Start > Con-Add-NoSpeech	Start utterance, no response, actions <b>with no speech</b>
	E=Con-Mov-Sother > Con-Mov-Sauthor > Speech-Shrt-Resp	Actions with speech and speech by others with <b>response</b>
	F= Con-Mov-Sother > Speech-Shrt-Resp > Speech-Shrt-Assen	Action with speech by others with <b>response</b>
	G= Speech-Full-Resp > Speech-Shrt-Resp > Speech-Shrt-Resp > Speech-Full-Resp	Conversation
	H= Indmap-Open-Sother > Speech-Full-Start	Open map and speech
Linking	I= Speech-Shrt-Start > Speech-Shrt-Resp>Con-Mov-Mult-NoSpeech> Speech-Shrt-Start	Start utterance, with short response
	J= Link-Add-NoSpeech > Con-Mov-NoSpeech > Link-Mov-Mult-NoSpeech > Link-Mov-NoSpeech > Con-Mov-NoSpeech	Actions <b>with no speech</b>
	K= Link-Add-NoSpeech > Con-Mov-NoSpeech > Link-Rem-NoSpeech > Con-Mov-Mult-NoSpeech	Actions <b>with no speech</b>
	L= Link-Mov-NoSpeech > Link-Rem-NoSpeech > Con-Mov-NoSpeech > Link-Add-NoSpeech	Actions <b>with no speech</b>
	M= Speech-Shrt-Resp > Speech-Shrt-Resp > Speech-Full-Start > Speech-Shrt-Assen	Conversation
	N= Con-Mov-Sother > Speech-Shrt-Start > Speech-Full-Resp	Action with speech by others with <b>response</b>
	O= Con-Mov-Sother > Speech-Shrt-Assen > Con-Mov-Sauthor	Actions with speech and speech by others with <b>response</b>
	P= Speech-Shrt-Assen > Indmap-Mov-Sother > Con-Mov-Sother	Speech, Open map and actions with speech

p&lt;=0.05

By contrast, high collaboration groups tended to combine physical actions performed with speech from the same author or other learners (*Sauthor-Sother*); and sequences of utterances that can be associated with conversation patterns (patterns G and M). Another trend is the keyword *Start* followed by a *Response*, or at least some verbal reaction in both phases of the activity (patterns E, F, N and O). Pattern H shows that in the brainstorming phase, these students tend to open their individual maps and follow this action with long speech activity. A similar pattern in these high collaboration groups was found for the linking phase, with the difference that the speech was accompanied by physical actions (see pattern P). It is not clear how they interacted with these individual maps hence the need of further exploration in our Research Question 5.

Table 7-10 Proportions of keywords in frequent patterns by using Alphabet 2.

	Collaboration	Speech	Start	Resp	Assen	NoSpeech	Sauthor	Sother
Phase 1 (brainstorming)	High	<b>83%</b>	<b>43%</b>	<b>60%</b>	25%	10%	6%	43%
	Low	27%	14%	12%	10%	<b>77%</b>	2%	<b>14%</b>
Phase 2 (linking)	High	<b>59%</b>	45%	<b>45%</b>	13%	39%	2%	19%
	Low	12%	7%	8%	1%	<b>94%</b>	2%	8%

p&lt;=0.1

Table 7-10 shows the proportion of appearance of keywords in the rest of the patterns that met the differential criteria. The presence of verbal utterances, and especially, responses to other students, distinguished high from less collaborative groups in both phases (60% and 45% of the patterns in high groups had at least one responding utterance *-Resp-* respectively, in contrast to just 12% and 8% of patterns for the corresponding phases in the low groups). Short assenting verbal utterances by learners, while another learner was speaking, were more common in more collaborative groups (*Assen*= 25% for high and 13% for low collaboration). This confirms the differences suggested in the examples described above.

*Question 4: Can we distinguish more collaborative from less collaborative groups based on patterns involving traces of interaction of students with others' objects?* After running the DSM algorithm using Alphabet 3 we obtained a total of 174 patterns. Table 7-11 presents the top differential patterns. It shows that the main distinction, for ownership and interaction, was not between high and low collaborative groups but between phases.

Table 7-11 Top sequential patterns found using Alphabet 3.

		Top-4 most differential patterns	Description
Brainstorming	Low collab.	A= Obj-Mov-Owner-NoSpeech>Obj-Mov-Owner-NoSpeech > Obj-Mov-Owner-Mult-NoSpeech>Obj-Mov-Owner-Mult-NoSpeech > Obj-Mov-Owner-Mult-NoSpeech	Actions on <b>own</b> objects, <b>no speech</b>
		B= Obj-Add-Owner-Sother > Obj-Add-Owner-NoSpeech > Obj-Add-Owner-NoSpeech > Obj-Add-Owner-NoSpeech	Actions on <b>own</b> objects, <b>some speech</b>
		C= Obj-Add-Owner-NoSpeech > Obj-Add-Owner-NoSpeech > Obj-Mov-Owner-NoSpeech> Obj-Add-Owner-NoSpeech >	Actions on <b>own</b> objects, <b>no speech</b>
		D= Obj-Mov-Owner-Mult-NoSpeech > Obj-Mov-Owner-NoSpeech > Obj-Mov-Owner-Mult-NoSpeech > Obj-Add-Owner-NoSpeech	Actions on <b>own</b> objects, <b>no speech</b>
	High collab.	E= Obj-Mov-Owner-Sother > Obj-Mov-Owner-NoSpeech > Obj-Mov-Owner-Mult-Sother	Actions on <b>own</b> objects, <b>no speech</b>
		F= Obj-Add-Owner-Sother > Obj-Mov-Owner-Mult-Sother > Obj-Add-Owner-Sother	Actions on <b>own</b> objects, <b>others' speech</b>
		G= Obj-Add-Owner-Sother > Obj-Rem-Owner-Sother > Obj-Add-Owner-Sother > Obj-Add-Owner-Sother	Actions on <b>own</b> objects, <b>others' speech</b>
		H= Obj-Mov-Owner-Mult-Sauthor > Obj-Mov-Difowner-Sother > Obj-Mov-Owner-Sother	Actions on others' objects, <b>others' speech</b>
Linking	Low collab.	I= Obj-Add-Owner-NoSpeech > Obj-Mov-Difowner-NoSpeech > Obj-Mov-Difowner-NoSpeech > Obj-Add-Owner-NoSpeech >	Actions on others' objects, <b>no speech</b>
		J= Obj-Mov-Difowner-NoSpeech > Obj-Mov-Difowner-NoSpeech > Obj-Mov-Difowner-NoSpeech > Obj-Add-Owner-NoSpeech > Obj-Mov-Owner-NoSpeech	Actions on others' objects, <b>no speech</b>
		K= Obj-Mov-Difowner-Mult-NoSpeech > Obj-Mov-Difowner-NoSpeech > Obj-Mov-Difowner-NoSpeech > Obj-Add-Owner-NoSpeech	Actions on others' objects, <b>no speech</b>
		L= Obj-Mov-Difowner-NoSpeech > Obj-Mov-Difowner-NoSpeech > Obj-Mov-Difowner-NoSpeech > Obj-Add-Owner-NoSpeech	Actions on others' objects, <b>no speech</b>
	High collab.	M= Obj-Mov-Owner-Sauthor > Obj-Mov-Owner-Sother > Obj-Mov-Difowner-Sother	Actions on others' objects, <b>own and others' speech</b>
		N= Obj-Mov-Difowner-Sother > Obj-Mov-Difowner-Sother > Obj-Add-Owner-Sother	Actions on others' objects, <b>others' speech</b>
		O= Obj-Add-Owner-Sother > Obj-Mov-Owner-Sother > Obj-Mov-Owner-Mult-NoSpeech	Actions on <b>own</b> objects, <b>others' speech</b>
		P= Obj-Mov-Difowner-Mult-NoSpeech > Obj-Mov-Difowner-Mult-NoSpeech > Obj-Chg-Difowner-NoSpeech	Actions on others' objects, <b>no speech</b>

p&lt;=0.05

These patterns suggest that most of the groups performed actions on their own objects during the brainstorming, without interacting with others' objects (no *Difowner* keyword in patterns from A to G). Only one of the top patterns shows that members of high collaboration groups also interacted with others' objects to some extent (pattern H). In line with previous findings, the speech also marked a difference between high and low collaboration groups (patterns F, G and H). For the *linking* phase we can see a prevalence of actions performed on objects created by others (*Difowner* keyword in most of the patterns in the linking phase). The more collaborative groups presented

strategies of less interaction with others' objects, combining interaction of students on their own objects with speech by the same learner or others.

Table 7-12 shows the proportion of keywords for the rest of the patterns. Both high and low groups have low physical interaction with others' elements during the brainstorming similarly to the example patterns (14% and 3% for *Difowner* respectively). Indeed, the low collaborative groups always performed actions on their own objects (100% for the keyword *Owner*). This suggests that the strategy of splitting the work, without verbally communicating with other members, is what most distinguished the low collaborative groups in the brainstorming phase. For the linking phase the patterns of the low groups had a higher level of interaction with others' objects (*Difowner* =83%). However, patterns for high collaboration group also had high rates of interaction with others' objects (*Difowner* =62%) in additional to patterns of speech.

Table 7-12 Proportions of keywords in frequent patterns by using Alphabet 3.

	Collaboration	<i>Owner</i>	<i>Difowner</i>	<i>NoSpeech</i>	<i>Sauthor</i>	<i>Sother</i>
Phase 1 (brainstorming)	Low	100%	<b>3%</b>	94%	1%	1%
	High	56%	<b>14%</b>	25%	22%	97%
Phase 2 (linking)	High	95%	62%	66%	27%	40%
	Low	97%	<b>83%</b>	99%	0%	4%

p<=0.1

*Question 5: Can we distinguish more collaborative from less collaborative groups in terms of the actions that follow the access to others' knowledge structures?* To investigate the actions learners performed in association with accessing learners' maps, the analysis to address question 5 was different from the previous questions. Here, we only considered the actions that occurred while each individual concept map remained open. The statistics show a difference in the number of times groups accessed individual maps (145 for high and 102 for low groups); therefore, we expect to find more patterns in the high collaboration groups.

Table 7-13 Top sequential patterns found using Alphabet 4.

Top-4 most differential patterns		Description
Brainstorming	A=Indmap-Close > Indmap-Open > <b>Speech-Shrt</b>	Speech after opening map, taking turns
	B=Indmap-Open> <b>Speech-Full</b> > <b>Speech-Shrt</b> > <b>Speech-Shrt</b>	Speech after opening map
	C=Indmap-Open > <b>Speech-Full</b>	Speech after opening map
	D= <b>Speech-Shrt</b> > Indmap-Mov-Sother > Indmap-Close >Indmap-Open	Speech and open map, taking turns
	E=Indmap-Mov-Mult-Sother>Indmap-Close>Indmap-Open> <b>Speech-Shrt</b>	Speech after opening map, , taking turns
Linking	F=Indmap-Close > Indmap-Open > Indmap-Mov-Mult-NoSpeech > Indmap-Mov-NoSpeech	Opening map, <b>no speech</b>
	G=Indmap-Mov-Mult-NoSpeech > Indmap-Mov-NoSpeech > Indmap-Mov-Mult-NoSpeech	Move maps, <b>no speech</b>
	H=Indmap-Mov-NoSpeech > Con-Mov-NoSpeech-Pers > Con-Mov-NoSpeech-Pers	Move maps, <b>no speech</b>
	I=Indmap-Open>Indmap-Mov-Mult-NoSpeech> Indmap-Mov-NoSpeech> Indmap-Mov-NoSpeech	Opening map, <b>no speech</b>
	J=Indmap-Open > Indmap-Close > Indmap-Open > Indmap-Mov-NoSpeech	Opening maps one by one
	K=Indmap-Open > <b>Speech-Shrt</b> > <b>Speech-Shrt</b>	Speech after opening map
	L=Indmap-Open > Con-Mov-NoSpeech-Pers	Open map and action
	M=Indmap-Open > Indmap-Mov-NoSpeech > <b>Indmap-Open</b>	Open more than one map in parallel

p<=0.05

Table 7-13 shows the differential sequences for both groups. For the *brainstorming* phase, the less collaborative groups did not have any differential patterns meeting the *support* condition. By contrast, patterns of the more collaborative groups had high levels of conversation after students accessed their individual maps (see patterns B, C and E). Patterns also show evidence that students took turns to open and explore individual maps one after the other (*Open* and *Close* events in patterns A, D and E).

For the *linking* phase, the less collaborative groups had some patterns; however, unlike the dominant strategy followed by the more collaborative groups, these were mostly physical actions

(Move actions) without verbal interaction after accessing individual maps (*NoSpeech* keyword in the patterns F to I). In the *linking* phase, the high collaboration groups continued using the individual maps as a tool to drive verbal communication (pattern K) and they opened more than one individual map at the same time, possibly for comparison (pattern M). Against our *expectations*, the length of the patterns we found was not long enough to detect *add* events for concepts and links contained in those accessed individual maps. The keyword *Pers* was found in some patterns (H and L but this corresponded to *move* actions).

### 7.3.6. Distilling Frequent Patterns

As a result of applying the DSM technique it may be possible to find *too many* differential patterns or some that are very *similar*. Therefore, it may not be simple to determine the higher level meaning of such findings without further processing. To alleviate these redundancy and dimension issues, we took inspiration from the preliminary study presented in Section 4.4 and clustered the resulting patterns based on their *similarity*. This subsection addresses the Research Question 6: *Can we group patterns of interaction by interweaving student's verbal and physical participation and associate them with higher level group strategies?*

*Pre-processing and algorithm: Hierarchical Clustering*

We designed a modified version of the Agglomerative Nesting (AGNES) hierarchical clustering algorithm. It was implemented as follows:

1) Due to the multi-dimensionality of each sequence item, (each item can have up to 4 keywords) we define a *similarity criterion* to drive the clustering. This is performed by configuring the level of keywords that will be used to measure similarity between 2 patterns. To showcase the applicability of the approach, we explored two similarity criteria: i) focused on parallelism and turn taking - Alphabet 1 (*tsame*, *tother* and *tparallel* keywords), or ii) focused on speech – Alphabet 2 (*speech*, *nospeech*, *sauthor* and *sother* keywords). We explored these two alphabets because both add contextual information to each action regarding the interweaving of student's *verbal and physical participation*.

2) The hierarchical clustering step itself is performed in an iterative process that starts by considering each single pattern as a cluster. Then, a similarity matrix among clusters is generated by calculating the average distance between sequences of each pair of clusters (average-link inter-clustering distance) focusing on the keywords selected in the previous step. After this, the algorithm merges the most similar clusters into new clusters recalculating the similarity matrix and continuing the process until it produces one single cluster that contains all the sequences in the dataset.

3) To choose an *adequate* number of clusters we stop the iterations when their number matches the max threshold (parameter  $m \leq 10$ ). Then, the clusters that are still similar are merged (only if the intra-clustering distance of the new cluster is not higher than the maximum internal distance of the largest cluster).

4) Finally, for each cluster, the sequence that has an *average length* and contains the *majority of the top keywords* found within each cluster is chosen as the *representative sequence* of the cluster. Final clusters with only one sequence are not included in the results. The result of this technique is a short list of clusters of sequences within each dataset (highly and weakly collaborative).

#### *Results*

As stated in the previous section, after the DSM algorithm was applied we obtained a total of 88 and 453 frequent patterns respectively that were differential ( $p < 0.1$ ). The next step was to cluster similar patterns using the AGNES clustering technique described above. Table 7-14 shows the resulting clusters using two similarity criteria: i) focused on parallelism and turn taking, and ii) focused on speech. In the case of clusters obtained by focusing on the sequence and authorship of touch actions, we found 5 clusters for the highly collaborative groups (c1-5). Similarly to the previous



case, the two larger clusters are associated with long chains of conversation (c1) or conversation accompanied with some touch actions (c2). Clusters c3 and c4 show chains of actions performed by the same learner in a row. This information is shown by the presence of the keyword *Tsame* (highlighted in Table 7-14) in the sequences. The smaller cluster is c5 shows sequences of actions performed by different learners; an indication of what we call *turn-taking* (*Tother* keyword). In the case of weakly collaborative groups, the size of the clusters had the opposite order compared to highly collaborative groups. The largest clusters mostly contains sequenced actions with the keywords *Tparallel* and *Tother* (c6 and c7), that are evidence of more parallelism and turn-taking in the weakly collaborative compared with the highly collaborative groups. Cluster c-9 shows some conversational patterns in these groups.

Regarding the role of speech in learner's strategies at the tabletop, highly collaborative groups had two main clusters: cluster-c10 with sequenced speech actions (utterances, highlighted in Table 7-14) and cluster-c11 with an interweaving of physical actions with speech performed by other learners (*Sother* keyword). For weakly collaborative groups, the clusters were: c12 that contains mostly sequences of touch actions without speech (*Nospeech*, highlighted in Table 7-14) and, to a much lesser extent, compared with the highly collaborative groups, clusters associated with conversational patterns and interweaving of actions with some speech (c14 and c15).

Table 7-14 Clusters generated

Clusters: focused on turn-taking and parallelism			
High collaboration	Representative sequences	Strategy	#
C1-{Speech}>{Speech}>{Speech}>{Speech}>{Speech}>{Speech}>{Speech}		Long conversation	246
C2-{Speech}>{Con-Mov-Tsame}>{Speech}>{Speech}>{Speech}		Chain of conversation	145
C3-{Con-Mov-Tsame}>{Link-Add-Tsame}>{Link-Chg-Tsame}		1 learner actions	36
C4-{Speech}>{Con-Mov-Tsame}>{Link-Add-Tsame}>{Speech}>{Speech}		1 learner actions and speech	20
C5-{Link-Add-Tsame}>{Con-Mov-Tother}>{Link-Mov-Tother}		Turn-taking	6
Low collaboration			
C6-{Con-Mov-Tparallel}>{Link-Mov-Tother}>{Con-Mov-Tparallel}		Parallelism	34
C7-{Con-Mov-Tother}>{Con-Mov-Tother}>{Link-Add-Tsame}		Turn-taking	27
C8-{Speech}>{Con-Mov-Tparallel}>{Speech}		Speech and parallelism	5
C9-{Con-Mov-Tother}>{Speech}>{Speech}>{Speech}>{Speech}		Chain of conversation	4
Clusters: focused on speech			
High collaboration	Representative sequences	Strategy	#
C10-{Con-Mov-Sother}>{Speech}>{Speech}>{Speech}>{Speech}>{Speech}		Chain of conversation	269
C11-{Speech}>{Speech}>{Con-Mov-Sother}>{Link-Add-Sother}		Actions and others' speech	144
Low collaboration			
C12-{Con-Mov-Nospeech}>{Link-Add-Nospeech}>{Con-Mov-Nospeech}		Actions with no speech	72
C13-{Speech}>{Speech}>{Con-Mov-Nospeech}		Speech and actions	9
C14-{Con-Mov-Sauthor}>{Speech}>{Speech}>{Speech}>{Speech}		Chain of conversation	4
C15-{Con-Mov-Sother}>{Con-Mov-Sother}		Actions and others' speech	3

# number of frequent patterns included in the cluster

### 7.3.7. Discussion

The *statistical exploration* of several indicators of interaction presented in Section 7.3.2 suggested that there were differences in groups' interaction based on their level of collaboration. However, such aggregate information at the end of the group activity has serious limitations. First, the statistical differences between the measures for the high or low collaboration were not significant. So they were not powerful enough to capture the differences. In addition, since they were only available at the end of the session, they would not be a useful basis for informing a teacher of potential problem groups during a class.

First, the overall approach begins with our classification method that proved effective in identifying 85% of the triads' level of collaboration. The classification was not infallible but it offered promise to provide an acceptable rate for automatic differentiation of groups' activity. The next technique applied was the DSM which generated a large number of patterns, especially for the highly collaborative groups. Our AGNES hierarchical clustering algorithm served to analyse the

relationship of speech and touch within highly and weakly collaborative groups and address our research questions.

Second, more specifically, by applying Alphabet 1, we discovered that the less collaborative groups had more patterns with physical interactions, high levels of physical concurrency and greater parallelism than the more collaborative groups. By contrast, the more collaborative groups had more verbal discussions in conjunction with physical actions, especially in the brainstorming phase. They also showed less concurrency in the physical dimension and less parallelism. This seems consistent with these students being more aware of their peers' actions and also making use of group discussions about the actions performed on the group map.

Third, we explored in more detail the patterns of verbal participation through the Alphabet 2. One of the most interesting findings for the less collaborative groups was the detection of patterns where a learner spoke briefly without getting a response from the other students. This aspect of communication is also considered by Meier et al. (2007), under the dimension of mutual understanding. For groups to maintain mutual understanding, they need to provide verbal feedback on their understanding in the form of an appropriate response, or by asking for clarification. In line with this, the more collaborative groups had higher rates of responses after other learners had spoken. These groups also had patterns of physical actions accompanied by speech by other learners. This is also consistent with these students being more aware of others' actions and discussion about each other's actions.

Fourth, the findings from applying Alphabet 3 to inspect interactions of students with others' objects partly contradicted the analysis presented earlier in Section 6.4. We found that the more collaborative groups had some interaction with others' objects in the brainstorming phase but in the linking phase, the less collaborative groups interacted more with other's objects.

Fifth, we explored the patterns of actions that occurred after students opened their individual concept maps to share them with others or to recall what they had done in the initial private mapping activity (Alphabet 4). We found evidence that suggests that the more collaborative groups accessed their individual maps to trigger discussion. Their actions showed that they either opened one map after another, or opened at least two concept maps simultaneously for possible comparison. For the less collaborative groups, our data does not really show how they used their individual maps. Contrary to what we had expected, the patterns found did not show the addition of concepts or propositions from those maps. This may be explored further by refining the alphabet.

Sixth, the clustering technique applied on the frequent patterns of verbal and physical interactions (alphabets 1 and 2) proved helpful in grouping numerous patterns in order to facilitate their association with high level observable student's strategies. In this way this approach can be used to distil information for teachers to derive their own conclusions.

### 7.3.8. Section Summary

**In this section we presented the design of an approach to explore whether we could distinguish high and low collaboration groups, by exploiting the affordances of our enhanced tabletop with COLLAID.** The approach can *automatically* distinguish groups according to their level of collaboration, mine the frequent sequential patterns that differentiate these, and then group the patterns to associate them with higher level strategies. We validated the approach through a study that involved the participation of 20 triads building concept maps and by addressing 6 research questions about collaborative work. Overall, the indicators of physical activity and verbal participation, produced by the implementation of our approach, are modest, if not limited, when compared with a full qualitative analysis of the utterances that can be carried out by an observer. However, our study showed that this approach has potential to serve as a basis for a further development of automatic support systems for students or monitoring tools for their teachers.

In this section, our approach was limited to group's collaboration as the main outcome of group work, without taking into account the quality of the concept maps they built. The next section

precisely addresses aspects of the digital concept maps built by students individually and as a group. Through this, we show that our Conceptual Framework, the same Learning Environment, and even the same dataset, can help address very different research questions.

## 7.4. Analysing Traces of the Student's Products

This section presents an approach to analyse the flow of knowledge that is shared, *created and acquired*, that occurs when students construct a concept map as a group, aided by our system. To achieve this goal, our work aims to exploit the activity logs that can be obtained during both the individual as well as from the collaborative concept mapping phase<sup>1</sup>.

Similarly to the analysis of student's interactions (addressed in the previous section), the information about the flow of knowledge that is shared, and its relationship with group's collaboration, can help teachers be more aware about their learning performance, the knowledge domain and their collaborative processes. The main contributions of this section are the approach to study individual and collaborative concept mapping; and the analysis of knowledge acquisition and collaboration by tracking the flow of use of propositions.

### 7.4.1. Research Questions

For this analysis, we investigated questions regarding the flux of knowledge that is shared or acquired from individual concept mapping construction during the collaborative sessions. The first question investigates the correlation between *individual contribution* and *change in the personal perspectives*.

1. *Is there a positive correlation between the number of propositions included by one student to the tabletop group map and the resistance to change in their individual perspective?*

In other words, do students who contribute more to the *group* concept map at the tabletop show less change in their perspectives after the group concept map building task, whilst those contributing less modify their perspectives more, appropriating new information from the group.

The second question investigates the level of agreement among group members by taking account only the student's products. We seek to learn whether building a group concept map at the tabletop makes an observable impact on the shared knowledge and persists after the activity. The second question is:

2. *Is there more agreement among group members after building a group concept map at the tabletop?*

The third question investigates the relationship between the extent of collaboration (that can be obtained automatically – as described in Section 7.3.4, or from qualitative observations – as described in Section 7.2.4) and the new knowledge created as a result of the collaborative activity. The theory of Group Cognition and a wide range of studies on collaboration indicate that one of the main outcomes of healthy collaborative interactions is the generation of “new knowledge”. This takes the form of ideas that were not present in the initial individual perspectives (concept maps) but are acquired by the group cognition (Stahl, 2006). We aim to validate that this can be reflected by the concept maps. The third question is:

3. *Is there a positive correlation between the extent of collaboration of a group and the new knowledge represented in the group concept map?*

The fourth question is inspired by the notion of constructive-conflict in CSCL systems (Prata et al., 2009; Roschelle and Teasley, 1995) by investigating the relationship between the similarity

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<sup>1</sup> Parts of this section have been published in the proceedings of CMC2012 (Martinez-Maldonado et al., 2012c).

among individual perspectives in each group and the new knowledge created as a result of the collaborative activity. We aim to validate this by inspecting the concept maps only. The fourth question is:

4. *Is there a negative correlation between the similarity of perspectives among group members and new knowledge represented in the group concept map?*

In other words, those groups in which the group members have divergent points of view about the topic will come up with more conflicting ideas that will drive the generation of completely new ideas in the form of propositions that were present in the initial concept maps of any of the group members before the group session.

### 7.4.2. Data Description and Measures of Similarity and Collaboration

The data used in this study includes all seven concept maps built by each group. These are the three maps built by each student initially ( $m_1, m_2, m_3$ ), the group map built at the tabletop ( $m_g$ ), and the three post-individual maps ( $m'_1, m'_2, m'_3$ ) (see Figure 7-15).

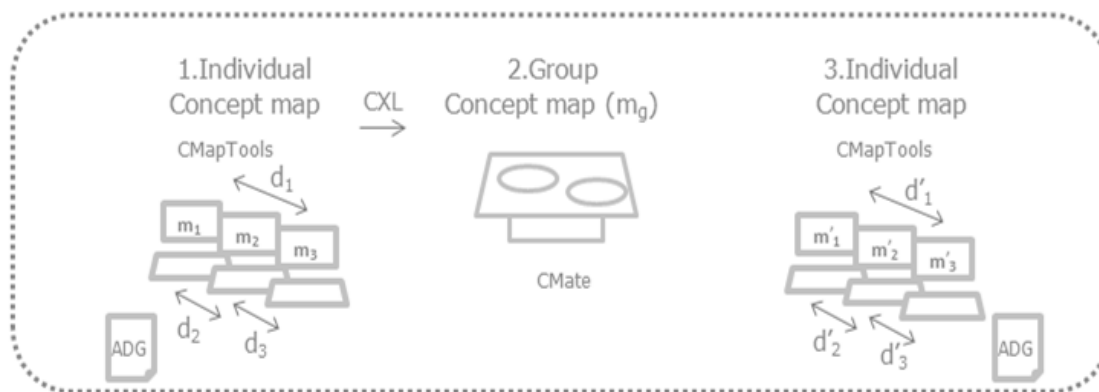


Figure 7-15 Approach. 1) Pre-individual concept mapping (creating  $m_1, m_2, m_3$ ), 2) Group concept map ( $m_g$ ) and, 3) Post-individual concept mapping (creating  $m'_1, m'_2, m'_3$ ). Where  $d(m_i, m_g)$  = similarity of pre-individual maps and the group map;  $d(m'_i, m_g)$  = similarity of post-individual maps and the group map;  $d_1, d_2, d_3$  = similarity among pre-individual maps of a group;  $d'_1, d'_2, d'_3$  = similarity among post-individual maps of a group.  $d(m_i, m'_i)$  = similarity between each pre- and post individual map per student. ADG = One-page Australian Dietary Guidelines.

To respond to the questions, a measure of similarity between concept maps was implemented. We adapted a technique inspired by the method for scoring open-ended concept maps developed by Taricani et.al. (2006). This technique is based on the use of a two-dimensional graphic network representation of a concept map, considering that this can be reduced to a relationship matrix. Then, finding the distance between two given matrices is a straightforward approach since the smallest Euclidean distance is used to identify the closeness of vectors. In the original method, the relationship data is compared with a referent master concept map to produce a score that represents how “similar” the assessed concept map is to the master map.

This automatic technique proved successful and very close to ratings performed manually by a human. In our study, this technique is used to automatically measure the similarity or “distance” between the propositions contained in any 2 concept maps. In this way, we calculate the similarity between each student’s pre- and post-concept map ( $s_1, s_2, s_3$ ), the distances between the individual concept maps of each group that were built before ( $d_1, d_2, d_3$ ) and after ( $d'_1, d'_2, d'_3$ ) the group map, the distances between each pre- and post-individual concept map and the group map ( $dg_1, dg_2, dg_3$  and  $dg'_1, dg'_2, dg'_3$ ; using the grouped average  $Dg$  and  $Dg'$  respectively). We do not use any referent map and we do not consider *correctness* of the propositions.

Another important indicator needed for Questions 2 and 3 is the measure of the extent of collaboration. We used the model to distinguish groups according to their level of collaboration

presented in Section 7.3.4 using a prediction Best-First tree. This model classifies each block of half a minute of activity, taking the average of the labels to define whether each group was collaborative or not. Table 7-15 presents the formulation of each question in terms of the measures of similarity ( $d$ ), level of collaboration (*collaboration*) and correlation ( $\rho$ ).

Table 7-15 Questions overview written as statements. The formulation of each refers to elements of Figure 7-15.

Statement	Formulation
1- Students who have more of their propositions in the group map well reproduce most of their initial concept map after the group session.	$\rho(d(m_i, m_g), d(m_i, m'_i)) > 0$
2- There is more agreement in the maps of group members after they build a group concept map at the tabletop.	$\text{Avg}(d'_{1,2,3}) < \text{Avg}(d_{1,2,3})$
3- Groups that are more collaborative generate more new knowledge represented in the group concept map.	$\rho((m_g - \{m_{1,2,3}\}), (\text{collaboration})) > 0$
4- Groups where students have more different individual maps generate more new knowledge represented in the group concept map.	$\rho((m_g - \{m_{1,2,3}\}), \text{Avg}(d_{1,2,3})) < 0$

### 7.4.3. Evaluation and Discussion

Next, we describe the evaluation of the questions listed above.

*Question 1: Is there a positive correlation between the number of propositions included by one student to the tabletop group map and the resistance to change in their individual perspective?*

A Pearson correlation coefficient was computed to assess the relationship between: the similarity of the pre-individual and the group map; and the similarity of the pre- and post- individual maps ( $\rho(d(m_i, m_g), d(m_i, m'_i))$ ). There was a positive correlation between the two variables,  $r = 0.503$ ,  $n = 60$ ,  $p \leq 0.0002$ . Students who contribute more to the group concept map, measured by the similarity between the pre-concept maps and the group map, present less change in their perspectives after the group concept map building task. This is indicated by higher similarities between the pre- and post- individual maps for each student.

At the other end of the spectrum, those students who did not contribute much to the shared concept map had significantly more change on their perspectives indicated by less similarity between their pre- and post- maps. This suggests that those students who tended to dominate the collaborative activity had more opportunity to influence others to modify their perspectives. This might be desirable if the high participants built a good concept map about the knowledge domain, but this might not necessarily be the case.

*Question 2: Is there more agreement among group members after building a group concept map at the tabletop?*

This indicates that the similarities among post-individual maps are higher than the similarities among pre-individual maps, as a result of the construction of the group map at the tabletop. This was calculated by comparing the averages of these distances per group as  $\text{Avg}(d'_{1,2,3}) < \text{Avg}(d_{1,2,3})$ . We found a very statistically significant difference for group map construction of these two conditions,  $t(19) = 6.73$ ,  $p < .0001$ .

Overall, groups increased their levels of agreement as a result of concept mapping at the tabletop. We further wanted to know if this increase in the level of agreement was greater for highly collaborative groups or for the less collaborative ones. In fact, we found that the less collaborative groups had higher levels of agreement after the tabletop session ( $t(8) = 7.86$ ,  $p < .0001$ ). For the less collaborative groups, the average similarities jumped from 0.29, for the pre-concept maps, to 0.50 for the post-concept maps. For the collaborative groups the agreement moved from 0.30 to 0.43 ( $t(10) = 3.67$ ,  $p < .0043$ ).

These findings could suggest a contradiction with theories on collaboration that affirms that one outcome of collaborative work is the establishment of common ground and possible agreement on the same group perspective (Stahl, 2006). Nevertheless, this is not necessary true, at least for

concept mapping, since one or two group members may convince others to change their perspectives or dominate the activity in such a way that collaboration is less effective. In our study, students who belonged to less collaborative groups tended to appropriate more of the group propositions than those in collaborative groups.

*Question 3: Is there a positive correlation between the extent of collaboration of a group and the new knowledge represented in the group concept map?*

The relationship between the quantity of new propositions created during the group task ( $m_g - \{m_{1,2,3}\}$ ) and the level of collaboration as indicated by the automated model was computed using Pearson correlation ( $\rho(m_g - \{m_{1,2,3}\}, (\text{collaboration}))$ ). We found a positive correlation between the two variables (collaboration and new knowledge created),  $r = 0.33$ ,  $n = 20$ ,  $p \leq 0.06$ . This correlation is not very strong though ( $p > 0.05$ ). A deeper analysis on the way collaboration is assessed should be carried out (e.g. by using video analysis in order to judge whether each group was indeed collaborating). However, there was not a strong tendency of collaborative groups to create more new propositions that were not considered individually.

*Question 4: Is there a negative correlation between the similarity of perspectives among group members and new knowledge represented in the group concept map?*

This question aims to find a relationship between the average of the similarity among pre-individual concept maps of a group ( $\text{Avg}(d_{1,2,3})$ ); and quantity of new propositions that were created during the group concept mapping task ( $m_g - \{m_{1,2,3}\}$ ). In this case, we found a weak negative correlation between the two variables,  $r = -0.36$ ,  $n = 20$ ,  $p \leq 0.059$ . This correlation is at the borderline thus it is not possible to make a statement from the results ( $p > 0.05$ ). Groups in which students showed more agreement tended to create less new knowledge, focusing more on the integration of the propositions that each of them had already created. On the other hand, groups in which their individual perspectives were more different from each other tended to create a new group map with more new content.

#### 7.4.4. Section Summary

**The four questions posed in this section sought to exploit evidence contained in the concept maps that can provide information about acquisition of propositions, knowledge creation and extent of collaboration of the group members.** The first finding (question 1) showed that students who actively contribute to the group work tend to convince others to adopt a similar point of view; therefore, these students are inclined to maintain their perspectives. Those who contribute least to the group map tend to change their individual perspective. A number of collaboration sub-processes can be involved in this effect for example elicitation, negotiation and conflict resolution.

The second question tackles a different angle of the group outcomes: agreement after the group activity. We found that after building a concept map at the tabletop group members built common ground and could individually represent parts of their shared artefact after the group work. However, a deeper analysis of this aspect showed that less collaborative groups strongly agreed after the group session. Examples of less collaborative group behaviours include the presence of a dominant student who performs most of the work without consulting others; independent work; having one student sub-participating or being just a free-rider (as it was described in the small-scale study in Section 6.2).

Question 3 links the level of collaboration with the amount of new knowledge generated. Studies on collaboration support a positive correlation between these two indicators (Stahl, 2006). However, the purpose of this question was to investigate whether the concept maps contain enough evidence to confirm this positive effect of collaboration. We found that, even though most of the high collaborative groups showed higher levels of communication, they do not necessarily reflected it in their concept map. The range of possibilities is wide: some of the better ideas may not have been translated into propositions, partial solutions may be higher quality than the final concept map or simply the way students draw their concept map may not reflect their discussions.

Regarding Question 4, studies of collaborative learning have provided evidence that groups with more divergent points of view tend to generate more new ideas (Dillenbourg, 1998; Stahl, 2006). However, we could not find a strong negative correlation that would allow us to state that divergent points of view in the individual concept maps produces an increment on the new knowledge in the group concept map ( $r = -0.36$ ).

The study had some areas of improvement: simple text analysis was used to compare concepts and the usage of synonyms, writing errors or slight changes in the words were not captured; the context of learning was not totally authentic. Students did not have to learn the content to get marks or pass a subject; students might have been affected by fatigue, especially after drawing the second individual concept map thus affecting the quality of their work; and the student population was chosen from a number of disciplines of science.

## 7.5. Chapter summary

This chapter implements parts of all the components of our Conceptual Framework (presented in Section 3.2) for a single-tabletop environment. We envisage that the work presented in this chapter provides a foundation for creating a system with the three main components of our TSCL framework:

1. the data capture system (DCF), to track and gather data of group activity;
2. the data analytics component (DAF), which is based on careful design of the alphabets that are a basis for producing group indicators via statistical and data mining techniques;
3. and the data presentation component (DPF), that aims to present to teachers, researchers or students visual information or knowledge about the collaborative process but which implementation goes beyond the scope of this paper.

The second set of outcomes of this study are the analysis techniques based on similarity measures, descriptive statistics, analysis of correlation, analysis of significance, analysis of artefacts (concept maps) and data mining. This analysis proved effective in addressing six research questions regarding patterns of interaction and four questions regarding properties of student's products.

We list the lessons learnt in this chapter:

1. *Quantitative student's data can be exploited to automatically provide a notion of group's level of collaboration at the tabletop.* We used a decision tree to classify episodes of activity based on quantitative dimensions of verbal and touch learner's actions and how symmetric these were. This method proved effective in identifying 85% of the triad's level of collaboration. The classification was not infallible but it offered promise for an acceptable rate to consider the feasibility of automatic differentiation of group's activity.
2. *Student's interactions can be analysed to find sequential patterns that characterise groups according to their 'level' of collaboration.* The next technique applied was the DSM (2012) which generated a large number of patterns, especially for the highly collaborative groups. In this way, we found some strategies that differentiate high collaboration groups based on their high levels of speech with and without physical activity. We found that the sequenced actions with higher rates of parallelism, turn taking and touch activity with less speech characterised the weakly collaborative groups. However, we can find hundreds of these patterns making it hard to understand the meaning of each of them.
3. *Clustering patterns of group interaction can provide a more effective way to interpret their higher level meaning.* Many patterns can be found from student's data, but it is not very easy to understand their higher level meaning. Our modified AGNES hierarchical clustering algorithm allowed us to distil the information making it easier to associate groups of patterns with high level strategies that characterised either high or low collaboration groups.



4. *Student's learning products can provide key information about how student's share their individual perspectives and acquire new knowledge from others or from the group.* Finally, we presented the analysis of artefacts, in the form of measures of similarity of concept maps, to investigate the transfer and creation of knowledge among students and the impact of their collaborative interactions.

The patterns we discovered are important at multiple levels. First, they demonstrate that we have achieved our overall goal to exploit the digital footprints of learners at our tabletop. Importantly, this work provides a foundation for creating interfaces for bringing the collaboration quality to the attention of the stakeholders. This includes learners in the groups. It has the potential to be particularly valuable for teachers who need to manage several groups in a classroom. It also provides researcher insights more broadly.

Overall, the indicators of physical activity and verbal participation, produced by the implementation of our approach, are modest, if not limited, when compared with a full qualitative analysis of the utterances that can be carried out by an expert human observer. However, we argue that our study provides evidence that our approach can serve as a basis for further development of automatic supporting systems for students or monitoring tools for their teachers. We designed each alphabet to correspond to the elements of a specific research question and therefore, each provides different information. This range of insights about collaboration cannot be obtained through a single alphabet that simply aggregates all the keywords. This would only lead to very long item-actions. It would be harder to interpret, and more difficult for the algorithm to discover patterns, given the higher variability of contextual information that would have to be analysed at once. The formulation of other questions requires different, new alphabets. The current work provides a basis for creating these.

Finally, the approach itself can serve as a basis for the design of interactive tabletop systems for collaborative learning, enabling a new level of support. We envisage systems that can capture, analyse and present students' information in order to enhance awareness for teachers, researchers or back to the students themselves. Real-time visualisations of the group process can be designed for the teacher, either exclusively or shared with the students. For example patterns found can be used as a benchmark to compare against new groups' patterns. If we detect patterns associated with non-collaboratively strategies, the system can trigger an alarm in *real-time* to help teachers become aware of potential problems and so, may help them make more informed decisions about when to intervene with particular groups.

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## Chapter 8: Data Analytics of Collaboration in the Classroom

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*"The classroom of the future is not a room. ...  
the world becomes the classroom."  
—Ray Farley*

**Summary:** This chapter presents the driving goal for this thesis: bringing to the classroom, the provision of support for teachers, by enhancing their awareness of student's collaboration. This chapter describes MTClassroom, a multi-tabletop classroom designed to both capture the interactions of students working in small groups, and provide the teacher with the infrastructure to design, control, monitor and assess collaborative activities. The effectiveness of the implementation of the MTClassroom is validated in two consecutive semesters of authentic university level tutorials. We validate our approach by providing teachers with three data-driven products: i) key indicators for assessing the design of classroom activities; ii) *real-time* visual indicators to help them identify the group that most needs to be attended next; and iii) analysis techniques to discover interaction patterns that differentiate high from low achieving groups.<sup>1</sup>

### 8.1. Introduction

The classroom is a common environment in which the teacher can foster face-to-face collaboration skills acquisition by making use of small group activities (Leonard et al., 1997). Collaborative face-to-face activities can offer particular advantages compared to computer-mediated group work (Ocker and Yaverbaum, 1999). However, even in small group activities, it is challenging for teachers to provide students the attention that they may require and be aware of the process followed by each group (Race, 2001). Commonly, teachers try to identify the groups that are working effectively, to leave them to work more independently, and so to be able to devote time to groups needing their attention. In order to justify the integration of tabletops into the classroom, as with any emerging technology, they should provide additional support to teachers, going beyond what they can do without such technology (Cuban et al., 2001).

As was discussed in Section 2.3.5, pervasive shared devices have been used in some classroom contexts, in the form of multiple interactive tabletops that have the potential of providing teachers with new ways to control groups (AlAgha et al., 2010) and monitor student's progress (Do-Lenh,

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<sup>1</sup> Parts of this chapter have been published in international conference proceedings of ITS 2012– Interactive Tabletops (Martinez-Maldonado et al., 2012d), CSCL 2013 (Martinez-Maldonado et al., 2013a) and EDM 2013 (Martinez-Maldonado et al., 2013d).

2012; Kharrufa et al., 2013a). However, many questions remain unanswered, if multi-tabletop classrooms were available in each school, how would teachers plan and enact their activities to enhance learning and collaboration? How can they evaluate how the activities actually went compared with the plan? How can they monitor multiple groups of students working through these devices? This last question points at the slightly hidden and currently unexplored potential of interactive tabletops for capturing learner's *digital traces of classroom activity*, offering teachers and researchers the possibility to inspect the process followed by students in their small groups, the high level processes that occur in the class, recognise patterns of behaviour or tracing the enactment of the classroom activities.

This chapter presents the driving goal for this thesis: bringing to the classroom new forms of support for teachers, where these enhance their control and awareness of student's collaboration. Our approach focuses on analysing face-to-face collaboration data to offer the teacher a number of services that can support and enhance the *classroom orchestration*. As previously stated in Section 2.2.3, this approach focuses on four dimensions of the metaphor of *classroom orchestration*: *design/planning, regulation/management, adaptation/intervention* and *awareness*. Figure 8-1 shows that, similarly to Chapter 7, this chapter addresses a specific goal presented in Section 1.3: **developing the approach and building tools to enhance teacher's awareness of student's collaboration and the progress of their task in an authentic classroom.**

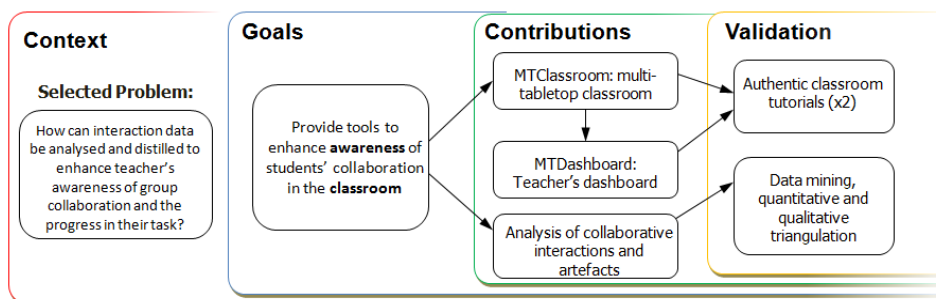


Figure 8-1 Context, goals, contributions and validation of Chapter 8.

In order to achieve this goal, we designed and deployed the MTClassroom (Figure 8-2), the first classroom enhanced by multiple interactive tabletop that facilitates *classroom orchestration*, unobtrusive data capture and the provision of real-time visual information about student's work. We use a teacher-driven approach to create the MTDashboard (Figure 8-3), an orchestration tool displayed on a handheld device that allows a teacher to control classroom activities and obtain live visual indicators of collaboration or progress of each group. The design, implementation and validation of these tools in authentic classroom situations, along with the analysis of collaborative interactions and student's artefacts, are the main contributions of this chapter.



Figure 8-2 Left: the MTClassroom. Right: CMATE being used in the classroom.

Regarding the TSCL-CF, the central focus of this chapter is the deployment of different components of the conceptual framework in an authentic classroom to generate awareness indicators for teachers and researchers to be used both in *real-time* and for post-hoc analysis.



Figure 8-3 A teacher with the MTDashboard in the MTClassroom.

Figure 8-4 shows the components of the TSCL-CF either investigated or applied in this chapter. The elements within the Data Capture Foundation (DCF) that were implemented in single-tabletop learning settings (refer to Chapter 7) are now deployed *in the wild*. The generation of indicators, and application of descriptive statistics and data mining techniques (Data Analytics Foundation, DAF), are implemented both to provide teachers with insights of group's progress and to trigger after class reflection. In addition, we complete the loop, by presenting the teacher with information about the classroom activities in real-time and for post-activity reflection (Data Presentation Foundation, DPF).

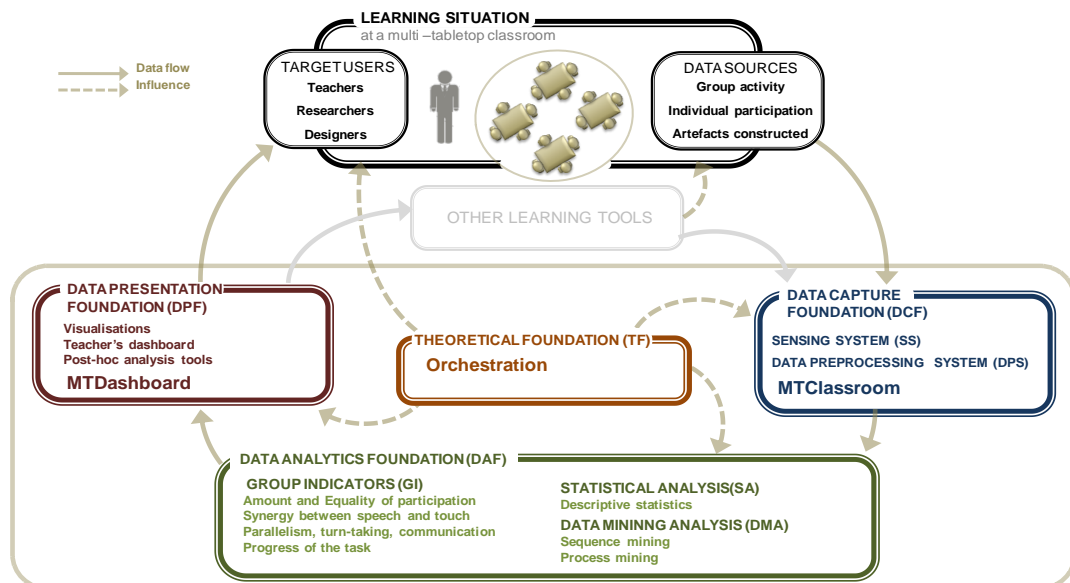


Figure 8-4 Studies in the MTClassroom in context with the TSCL-CF.

We validate the instantiation of the TSCL-CF in an authentic classroom by demonstrating the ways in which the MTClassroom can be used to provide the teacher with three different forms of information:

1. **Key indicators of the execution (enactment) of the planned classroom activities** to enable the teacher to assess the design of their class script;
2. **Real-time visual feedback of each small group performance;** and
3. **Data models of student's strategies** obtained through data mining and process mining algorithms.

The chapter is structured as follows. The next section presents the design guidelines that drove the construction of our educational technology, and the details of the software and hardware used to implement it. We also present the technological infrastructure of the MTClassroom; including the controlling and monitoring functionalities of the teacher's dashboard (MTDashboard). Section 8.3 describes the design and validation of a number of *key indicators of the enactment of the classroom*

*activities* that show how well the actual classroom practice adhere to the design of the teacher's script. This analysis is conducted on a first set of tutorials in which the MTClassroom environment was used. Section 8.5 presents a second set of authentic tutorials reflecting the re-design, which was informed by the results of the previous analysis. Based on this second set of tutorials, the Section 8.6 analyses the impact of presenting *real-time visual representations of each small group performance* on teacher's attention. Finally, Section 8.7 describes the analysis of sequences of student's actions, to discover patterns associated with group strategies that can differentiate groups according to their level of collaboration.

## 8.2. The Learning Environment: MTClassroom and MTDashboard

The MTClassroom learning environment provides a suite of hardware and software tools for (i) enabling students to work in small groups to build virtual artefacts in the form of concept maps that represent their shared understanding, and (ii) enabling teachers to orchestrate the learning activities and teach curriculum content. In this section we present the design and technical details of the MTClassroom and MTDashboard.

### 8.2.1. MTClassroom Design Guidelines

The main motivation for designing MTClassroom and MTDashboard is that, as the use of technology in and out the classroom is spreading, large amounts of learner data can be captured and summarised. These summaries can be exploited to show information that might otherwise not be easily available. This can be provided to teachers so that they can better decide where to devote their attention so that they give timely interventions (Bull et al., 2012). It is also valuable for later reflection on how their classroom attention was divided. Next, we describe the principles of *classroom orchestration* and awareness that drove the design of the educational technology presented in this chapter.

*Supporting the role of the teacher as the main actor in classroom orchestration.* The design of the system should primarily focus on providing services to assist teacher's actions and enhance their awareness in the classroom (Dillenbourg and Jermann, 2010). The teacher is the orchestrator of the learning activities, the class script, the technology and the whole learning experience. The technology should be designed to serve the teacher, so that they can perform the orchestration tasks more effectively.

*Supporting centralised and independent teacher classroom control.* All tabletops and other classroom technologies should be controlled by the teacher to some extent; this control should be simple and effective (Dillenbourg et al., 2011). This means that it should be minimalist, so as not to add cognitive load to the teacher. It must be well integrated in the classroom, so the teacher does not need to be distracted from their teaching tasks. It should not rely on designers, researchers or any other external technician.

*Supporting coordination of planned learning activities.* The tools should support the enactment of the activities designed by the teacher, so that the learning objectives can be achieved (Prieto et al., 2011). The technology tools should allow teachers themselves to design or adapt the learning activities according to the teaching objectives.

*Supporting classroom regulation and management.* The system should provide the teacher with functions to manage and adapt, to some extent, the macro script of the classroom activity (Dillenbourg et al., 2011). We also highlight the importance of after-class analysis of the data that can be captured during the learning activities for reflection, evaluation and further re-design of the learning activities to improve the enactment of future repetitions.



*Providing a user-friendly student user interface.* The student's interface should be simple, so that they can learn to use it within a few minutes, even on first use. This avoids wasting classroom time, an important resource in our context where a class session lasts only 50 minutes. If students require large amounts of time to learn how to use the interface, then the teacher would need to allocate a special training session. This can make the learning tool harder to be deployed in authentic classrooms.

*Capturing differentiated student's actions.* It is important to distinguish which student performed each touch. This is needed to automatically identify each student's contributions or group dynamics such as dominance, leadership or disengagement. It is also crucial to provide effective feedback to the teacher about each student's performance or to generate learner models.

*Capture and centralised gathering of the classroom activity.* Keeping track of all learners' differentiated actions in a centralised repository (e.g. a database server) is essential for creating monitoring tools that present overviews of student's actions or assess the match between the designed and actual enacted activities. These monitoring tools should be able to access the captured information *in real-time* and also make it available to the teacher for further activity re-design.

*Providing "light-weight" indicators about learner's progress.* The system should be able to automatically capture small group's interaction data and present this information to the teacher to enhance their awareness and direct their attention (Bull et al., 2012).

### 8.2.2. Technical Infrastructure (Hardware)

This section describes our technical infrastructure that consists of: the multi-tabletop classroom, the system for capturing user-identified actions and the system that interconnects the components of MTClassroom (tabletops, teacher's dashboard, vertical display and the data repository). Based on the guidelines listed in the previous section, we designed our multi-tabletop classroom. The MTClassroom is composed of 4 interconnected multi-touch interactive tabletops. These use 46" PQ Labs Multi-Touch overlays, placed over digital screens of the same size, which can detect up to 32 touches simultaneously (Figure 8-5, d). This is similar technology to that used in our previous studies.

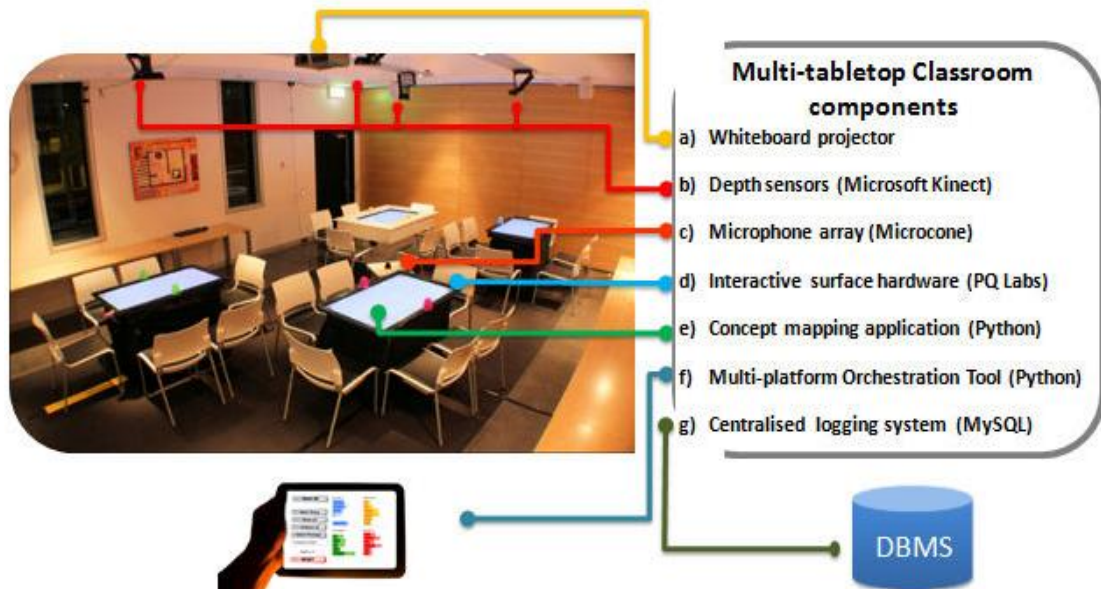


Figure 8-5 MTClassroom: Multi-tabletop classroom physical components.

All tabletops are enhanced with our system that detects the student who is touching the interactive surface, based on over-head depth sensors as described in Section 5.4 (see COLLAID in Figure 8-5, b; and Figure 8-6, left). In this way, the *host applications* running on the tabletops recognise and log differentiated actions performed by each student. In this learning setting, COLLAID

proved to be adequate in general terms, similarly to the controlled environment studied in Chapter 7, as students tended to stay seated at the same positions around the tablespots. A directional microphone array was placed at the centre of the four tablespots to detect levels of sound that each group produced (Figure 8-5, c) therefore the verbal participation of individual students was not considered for the studies presented in this chapter.

From the *teacher's perspective*, MTClassroom offers functionalities for orchestrating the tablespots through a controller dashboard that allows teachers to send commands to the host applications to trigger *actions* such as blocking the touch input or moving to the next learning phase. A full description of the design of this tool is provided in the next section. The system incorporates a connected wall projector that the teacher can use to display the artefact at a determined tabletop to support sharing, discussion and reflection at classroom level (Figure 8-5, a; and Figure 8-6, right)

From a *data capture perspective*, the system automatically differentiates student's actions at the tabletop according to their seating position. The logging system of each tabletop records the activity logs to a central synchronised repository that can be accessed in *real-time* by other services (Figure 8-5, g). One of these is the teacher's dashboard - MTDashboard (Figure 8-5, f). Additionally, *observation consoles* can be directly connected to the repository to capture synchronised qualitative data. In our study, two observers submitted standardised annotations of the *teacher's* attention and interventions. These consoles are described below.



Figure 8-6 Wide view of the MTClassroom. Left: The teacher attending one group. Right: Reflection driven by the teacher using the wall display.

### 8.2.3. Learning and Orchestration Tools (Software)

We created a set of interconnected software that makes the classroom operate as a single piece of technology, orchestrated by the teacher. Figure 8-7 shows the back-end infrastructure and the user interfaces that can be interconnected in the MTClassroom environment. The user interfaces that are visible to students or their teachers are the teacher's orchestration tool, the shared wall display and the host learning applications in each tabletop. A main orchestration server is used to coordinate the actions performed by the teacher (the real human orchestrator) to control the technology and the script of the learning activity. Next, we describe each of these elements in detail.

#### *Back-end and logging services*

**Orchestration Server.** The orchestration server is in charge of the core controlling, communication and logging activities in the MTClassroom. The main task of this element is to receive teacher's commands from the teacher's orchestration tool (displayed on a tablet for the studies presented in this thesis) and send, in response, a series of messages to the elements of the MTClassroom (to each interactive tabletop, the wall display or the database). The second main task of this element is to get information from the database to show *real-time* indicators of collaboration or student's performance to the teacher through the MTDashboard. In the studies of this thesis this information is shown only to the teacher, in the form of visualisations. However, this information could also be presented to students or be sent to other external systems such as web versions of teacher's dashboards or open learner models. The orchestration tool can have access to web-

services to perform actions on the data on-the fly. For example, we use Google charts to generate the live-visualisations of student's data. The orchestration server is also in charge of managing the mechanisms for performing learner's authentication to log and track each student's participation. For this thesis, these authentication mechanisms are fairly simple: students manually indicated their position at the tabletop on their name in the list. Further usage of MTClassroom, especially for a number of sessions in a course, should provide a more sophisticated solution. More details of possible ways to achieve this are discussed in Chapter 9.

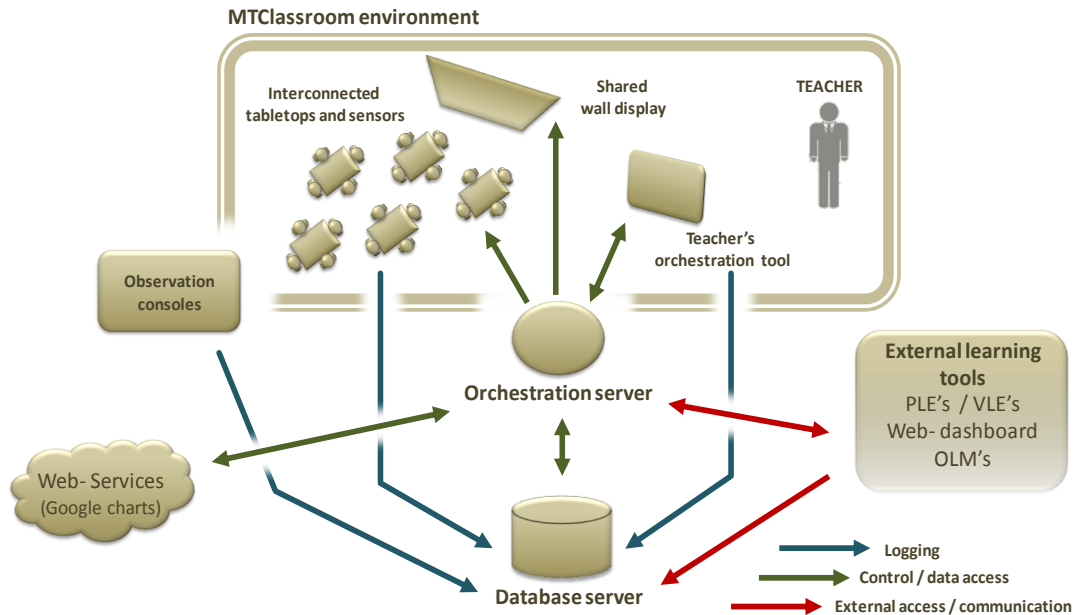


Figure 8-7 MTClassroom: Multi-tabletop classroom back-end and user interface components.

**Database server.** The use of a central data base server is crucial for effective student data collection. It provides both standard ways for recording, extracting and analysing information and also a simplified approach for synchronising data logs from multiple sources. These include activity logs of each table, teacher's actions on the orchestration tool or sensing information such as that produced by the microphone array. Additionally, this information can be accessed immediately through other services, making it possible to provide *real-time* information in the form of visualisations or through data mining or modelling techniques.

**Observation consoles.** Not only the sensors or the learning applications can generate activity logs but also observation consoles. In our study, two observations consoles were used to record all the teacher's actions and movements in the classroom and to rate levels of collaboration for each group. Importantly, these consoles record information directly to the central database so the observations are also synchronised with the rest of the activity logs of the MTClassroom. These are important for research purposes but are clearly not part of the core learning activities in the class.

**Connection with external learning tools.** The MTClassroom can be connected to external learning systems to receive information about student's previous learning activities and artefacts from PLE's or VLE's. Furthermore, the information about student's activities and their learning products can be exported to these systems to be used in further learning activities. The student's data, captured in the classroom, can be integrated into these external learning environments to help teachers monitor students' activities after the classroom sessions. It can also be used to generate visual information to be shown to the students to reflect on how well they performed or collaborated. For our studies, the MTClassroom could read an *exported* concept map built in CMap Tools. This was used by the teacher to create an *expected map* that was compared with student's maps in *real-time*.



### User interfaces

Our three main applications, visible to the users, are: the teacher's orchestration tool, the learning application displayed on each tabletop and the application that shows student's artefacts on the wall display.

*Teacher's orchestration tool (MTDashboard).* The tabletops are controlled by the teacher through the orchestration tool: the MTDashboard. The MTDashboard is a multi-platform teacher's tool that contains both controlling and awareness components (Figure 8-8, right). In this study, the dashboard was displayed at a handheld tablet device that the teacher carried while walking around the classroom to monitor student progress (Figure 8-8, centre). It can also be displayed on another tabletop, the teacher's laptop or a desktop computer. The design of this dashboard was driven by the requirements specified by the teacher in our studies. The design was also based on principles of *classroom orchestration* of regulation and awareness (Dillenbourg and Jermann, 2010; Prieto et al., 2011) and inspired by similar technologies applied in related work (Do-Lenh, 2012; Mercier et al., 2012). We used a participatory design process with iterative prototyping, with the teacher driving and responding to designs. This process identified the following components for the user interface.

A) *General functions*, commands that the teacher can use with any tabletop. These are, "Start" (Figure 8-8, A1) and "Finish" (A4) commands, to explicitly mark the boundaries of the activity by synchronously ordering all the tabletops to start the activity or finish to continue to the next activity; a "Send message" (A6) command, so the teacher can send text messages that appear in front of each student at all the tables about, for example, the time left for the activity; "Block" (A2) and "Unblock" (A3) commands to freeze the table for the teacher to get student's attention when needed, and does not want students distracted by using the tabletop (Figure 8-6-right, shows the teacher blocking the tabletops while she provides feedback to the class); and a "Reset" (A5) command to clean up the tabletop interfaces, making them ready for students in next tutorial.

B) *Configurable functions*, may be applicable for various activities but their meaning depends on the macro-script definition. These include the "Jump to the next phase" (B1) and "Send to the wall" (B2) commands. Figure 8-6 (right) shows a case where this action causes display of a concept map from one tabletop to the wall display.

C) *Awareness visualisations*, which can show key information about each group's progress, participation or other indicators that may be relevant for the domain. Teachers can configure the dashboard to display a visualisation of each group's activity, as shown at the right of Figure 8-8 (C). It can show, for example, a simple two-part bar that summarises the level of participation of each student in the activity, a participation radar (as shown in the figure) or other visual representations of different aspects of the group's solutions. The purpose is to help the teacher identify groups or group members who may have low levels of participation, collaboration or performance. More details of these visualisations are explained in the next sections.

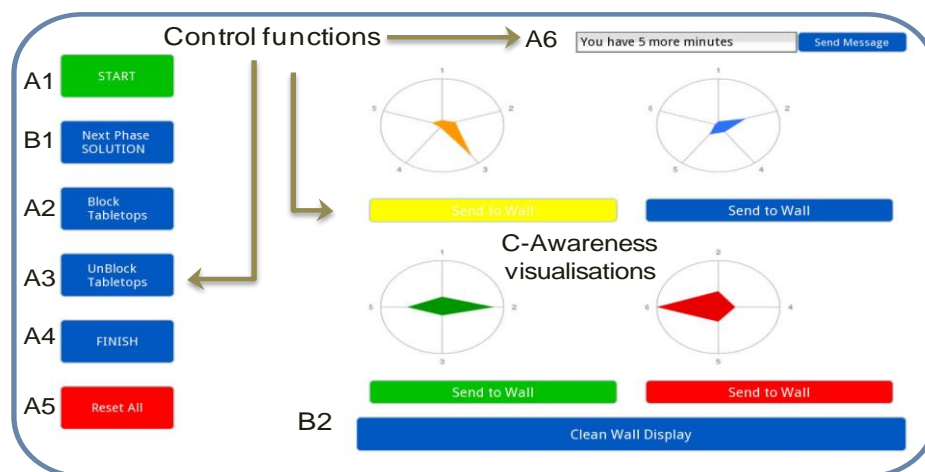


Figure 8-8 User interface of the MTDashboard (annotated to show Control functions A1-6, B1-2, C).

*Learning application.* MTClassroom can run different learning applications. In the studies described in this chapter we used a minimalist version of the final version of CMATE (refer to Table 5-2). Four interconnected instances of a minimal version of a *collaborative concept mapping application* are loaded onto each tabletop (Figure 8-9). In this case, CMATE provides students with a list of concepts and linking words that had been suggested by the teacher. It also allows students to type their own words, in order to build a concept map that represents their solutions to a posed problem. Prior to the classroom activity, the teacher can use the desktop concept mapping editor, CMapTools, to create the list of initial concepts and linking words, and generate a *Master Concept Map*. This Master map contains the *crucial concepts and propositions* that the teacher considers are important for learners to include in their maps in order to achieve the intended learning goals.

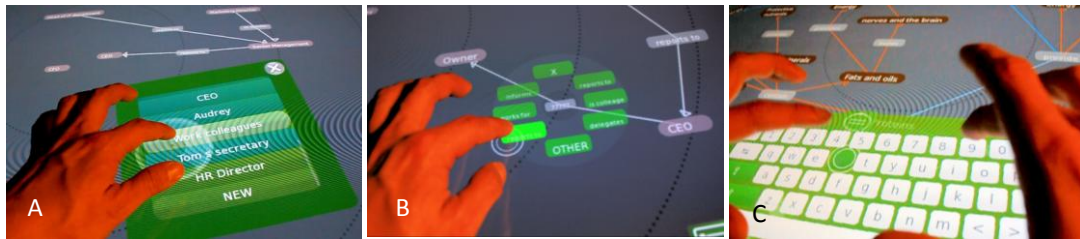


Figure 8-9 Minimal application for concept mapping

Users can create a complete concept map about a topic in minutes by performing three main actions: 1) *adding a concept*, by selecting it from an initial list concepts provided by the teacher (Figure 8-9, A); 2) *creating a linking word* that joins two different concepts, by dragging and dropping one concept onto the other, and then selecting a word from a list of suggested links (Figure 8-9, B); or 3) *editing a concept/linking word*, that is fired when a student dwells on any concept or link. This brings up a virtual keyboard in front of the user who performed the selection (as resolved by the depth camera) (Figure 8-9, C). Students can also *highlight* the links that they consider are important according to the learning task, by zooming in the linking word. Students can also perform other intuitive actions such as moving, deleting and resizing elements to create a concept map.

*Shared wall display.* The vertical display is used by the teacher to present instructions and explain the purpose of the learning activities as with any other classroom display. However, as shown above, the teacher can also use the MTDashboard to send the concept map created by a specific group to the wall display. This map is shown by a modified version of CMATE (CMATE-wall) which adapts the maps built on the horizontal surface to be displayed on a vertical device by rotating the text accordingly and highlighting the parts of the map as indicated by students.

## 8.3. Classroom Activity Design (Tutorials 1)

Two sets of tutorial sessions were taught in Semester 1 and 2, 2012, in the School of Business of the University of Sydney. This section focuses on the first tutorials. In the *first set* of 14 classroom sessions, our goal was to investigate how a teacher can design and orchestrate small group activities using the enriched classroom, and subsequently analyse the captured data to assess that design. The technology used in this preliminary study did not have any awareness tools. The control functions were available through the MTDashboard loaded on the teacher's personal computer. The study informed about the design of the tools needed to *orchestrate* and design classroom activities.

A learning activity was designed by the teacher to fit into one session of this first set of tutorial sessions with undergraduates in the unit: *Foundations of Management*. This has fifty minutes weekly tutorials that involve discussions of a previously defined case-study (see Appendix Section A.4.1). Tutorials are often run as a teacher-led class discussion or by organising students into small groups. The teacher decided to use interactive tabletops to support these small group discussions for the tutorials in Week 9. The unit had 236 students, scheduled into 14 tutorial slots. In each tutorial session small groups were formed to give diversity, in terms of gender and international versus domestic students, at each table. Students knew their peers well as they had met over several weeks before. In each tutorial session, there were at least three students per table and a maximum of six.

Data from sessions was captured, including: application logs with user information, snapshots of the evolution of each group's concept map solution, and the actions performed by the teacher on the orchestration tool. Figure 8-10 shows one of the sessions. During classes, the teacher moved freely among the tablespots, reviewing each group's concept map and identifying groups that needed help. Three semi-structured interviews were held with the teacher after the tutorials to investigate the teacher's observations of the enactment. One of these included the presentation of the results, described in the next section, to collect the teacher's reflections and considerations for future re-design. Additionally, we used participant's data, as well as observations, in order to capture teacher's intentions, actions and reflections.



Figure 8-10 Multi-tabletop classroom enactment

Importantly, the class design involved collaboration between the teacher and tabletop team to ensure that the design of the classroom activities was carefully crafted to make effective use of the multi-tabletops. Next, we describe the phases of the learning activity in terms of the timing, tools, tasks and learning objectives as intended for each repeated tutorial. Figure 8-11 shows the formalisation of the design using a representation developed by Prieto et al. (2009). This very concise form is gaining increased use by researchers to document orchestration plans. In this diagram we observe the actions to be performed by the teacher and the students at different social levels (the classroom and within each small group). Next, we explain each part of the design plan, with special emphasis on the various tools available and the atomic actions performed by the teacher during the enactment.

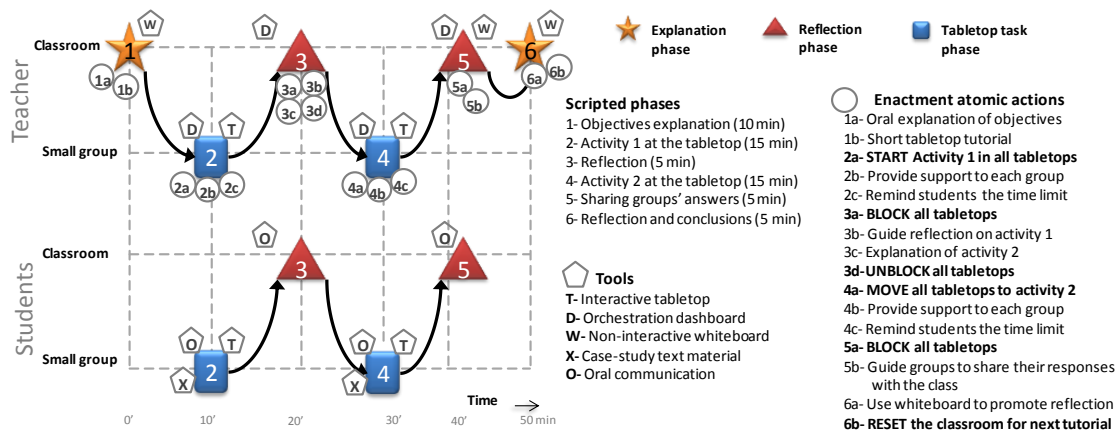


Figure 8-11 Design plan for the activity using the multi-tabletop classroom. This is scripted in 6 phases. Two are performed at the interactive tablespots (blue squares). The actors are students in small groups (lower), and their teacher (upper). The right half shows the phases, tools and atomic actions.

1. *Objectives explanation (10 minutes)*. First, the teacher explains the structure and goals of the tutorial (1a, Figure 8-11). The objective of the tutorial is to tackle a problematic scenario within an organisation. This is described in two pages provided to the students a week earlier, and which they have to read as preparation. Then, the teacher explains the main concepts of

the topic and how to use the tabletop application to build a concept map (1b). The teacher makes sure that students understand this by walking around and stopping to check each group.

2. *Activity 1 at the tabletop (15 minutes)*. For this activity, students are asked to *create a concept map that represents the case study organisational hierarchy and the stakeholder's power level*. This first concept mapping task enables students to establish shared understanding of their approaches to the problem, based on their preparatory reading and thinking. The tabletop application provides students with a list of the main *concepts* extracted from the text provided by the teacher (see Appendix Section A.4.2). These correspond to different role players within the organisation (e.g. CEO, HR Director, Low level staff). Students can also create their own new concepts. The provision of starting concepts is important for enabling the class to focus on the creation of the relevant propositions in the limited time available. The final map should contain the key concepts of the problem, their relationships and reflect the distribution of power within the organisation. The teacher starts the activity (2a), walks around reviewing progress and joins the discussion of some groups (2b). The teacher makes sure students are always updated on how much time they have left, by verbally reminding the class or by sending a message to all tabletops through the orchestration tool (2c).

3. *Reflection and connecting activities (5 minutes)*. After about 15 minutes from the start of *Activity 1* the teacher stops student's work by blocking all tabletops (3a), leads the reflection on *Activity 1* (3b), and then describes *Activity 2* (3c) explaining how it builds on *Activity 1*. When finished, the teacher unblocks all tabletops (3d).

4. *Activity 2 at the tabletop (15 minutes)*. To start *Activity 2*, the teacher uses the orchestration tool to send a command to all tabletops (4a). *Activity 2* called on students to *provide a new piece of information about the problem by modifying the concept map built in the Activity 1*. Students are provided with additional concepts and different linking words to use in new types of propositions. The teacher moves around the class, meeting each group (4b). The teacher can send a time limit reminder through the orchestration tool (4c).

5. *Sharing group's answers (5 minutes)*. After about 15 minutes of the *Activity 2*, the teacher stops students by *freezing* all tabletops (5a). The teacher asks each group to share their solutions with the rest of the class (5b).

6. *Reflection and conclusions (5 minutes)*. The teacher uses the notes on the whiteboard to summarise the key ideas students should take away from the tutorial and also to link it to the theories on this topic (6a). Then, the teacher resets all tabletops using the orchestration tool, ready for the next class (6b) that sometimes starts in the next 5 minutes.

Next, we describe the evaluation that highlights the affordances of our system for monitoring the match between teacher's intentions and the enactment of the 14 tutorials.

## 8.4. Supporting Teacher's Design and Design Assessment

Teacher's effectiveness in orchestrating the classroom has a direct impact on students learning. This section describes our mechanisms to help the teacher orchestrate the design of a classroom activity using multiple interactive tabletops. For this, we analyse the automatically captured interaction data to assess whether the *activity design*, as intended by the teacher, was actually followed during its *enactment*. This offers an approach for designing a multi-tabletop classroom that can help teachers plan their learning activities; and provide data for assessment and *reflection* on the enactment.

### 8.4.1. Practical Evaluation: from Design to Enactment

The purpose of this evaluation is to validate whether the MTClassroom can enable the teacher to evaluate how well the actual class matched the design intentions, particularly those that were specifically designed to exploit the tabletops affordances. Our approach did not simply adapt the

pre-existing learning activities to an interactive surface: this may not translate into an improved experience and can lead to forced activities that may not be effective for these devices (Coppin et al., 2011). One key part of the appeal for a teacher to undertake this project was the opportunity to evaluate the way *their own activity design* played out in the real classroom. Table 8-1 shows the teacher's design intentions (Column 2) and the data that our system captured that can be used to assess how well these intentions were met (Columns 3, 4). Teacher's intentions were grouped into three categories: *collaboration* and *equality* of student participation (A), the adherence to the class *script* over all the sessions (B), and the achievement of the *learning outcomes* (C). The first two aspects can be generalised and applied to other contexts. The *learning outcomes* are connected to the particular activity of concept mapping.

*Collaboration and equality.* Multi-touch tabletops offer equal opportunity for each user to provide input. One of the priorities for the teacher was to encourage group's collaboration. The intention of the teacher was that all groups could engage in productive discussions with all the students involved in the co-construction of the solution. The capture of this dimension of collaboration is beyond the scope of our system (Table 8-1, Rows A3, A4). Another more modest attribute of collaboration, that has proven to be important for teachers to be aware of, is the amount of participation of each student in their group activity (Kay et al., 2006). For this, our system can automatically analyse the balance of the physical participation (touches) and the contributions of each group member to the shared product (i.e. to the group map) (Table 8-1, Rows A1, A2). We used application logs and the analysis of group products to determine the equality within each group.

*Adherence to the class script.* The second set of teacher's intentions is associated with the effectiveness of the teacher to stay on track, following the planned sequence of activities (Figure 8-11) and the time limit restrictions. One possibility is that the time planned for a certain activity is actually an over or under estimate, so requiring a change in the design. It could also be the case that the teacher inadvertently modifies the way the script is followed for some sessions; therefore, impacting on student's learning. Interactive tabletops and the orchestration tools can improve awareness of the process the teacher actually followed in the classroom. We investigated three design intentions set by the teacher. The first two relate to the time the teacher spends on each activity (Rows B1, B2). The third design intention is about the student response to the time allowed for each activity (Row B3). The logs of the orchestration tool indicate the teacher's behaviour and the tabletop application logs show student's task progress.

Table 8-1 Teacher's intentions and data that captured from our system (A=Is it possible to assess it from the captured data?).

	Teacher's design intention	Data collected during the enactment	A
	<b>Collaboration and equality (general)</b>		
A1	Each member should participate equally to some extent	Equality in participation from application logs	YES
A2	Each member should contribute equally to the group solution	Equality in contribution from the final maps in activities 1 and 2	YES
A3	All groups should participate in in-depth group discussions	-	NO
A4	All groups should demonstrate collaboration between team members	-	NO
	<b>Adherence to the class script (general)</b>		
B1	Each class activity at the tabletop should take the planned amount of time	Orchestration logs show the duration of the activities and the impact on group's performance	YES
B2	The explanation and reflection phases should keep to the time	Orchestration logs show the duration of the phases and the impact on the duration of the activities	YES
B3	All groups should start discussing and visually representing their ideas as soon as the tabletop activities start	Application logs show the time and evolution of the physical construction of group's products	YES
	<b>Learning outcomes activity 1 (concept mapping)</b>		
C1	All groups should identify the key concepts of the topic and their relationships, and avoid irrelevant concepts.	Application logs show the key concepts and relationships created by each group	YES
C2	All groups should understand the power distribution of the key concepts/players of the case	Final products logs indicates the physical arrangement of objects in the tabletop surface indicating power distribution	YES
C3	All groups should have discussions of different possible solutions and be able to justify their solution	-	NO

*Learning outcomes of activities 1 and 2.* Two learning goals were set for the tutorials. The aim for the first activity was two fold: students should identify the key concepts of the case problem and visually represent the relationships between them (C1) and the distribution of power within the example organisation (C2). The tabletop application can validate the concepts and the propositions contained in each group map by comparing them with a *master map* (see Appendix Section A.4.3). This contains the key concepts, linkages and hierarchical layout that the teacher expected from student's maps. For *Activity 2*, the learning goal was to discuss possible solutions to the case and justify why they chose their final solution for the situation within the example organisation, by augmenting the concept map produced in *Activity 1* (C3).

## 8.4.2. Results and Teacher's Reflection

We now report results of the evaluation of the teacher's design intentions based on data from the 196 students, who agreed to make their interaction data available. They were organised into 40 groups: 10 had six students, 17 had five, 12 had four and 1 had three. Data from interviews with the teacher, as well as from non-participant observations were used to triangulate evidence.

### *Collaboration and equality*

*Each member should participate equally (A1).* We assessed whether physical participation and contribution were balanced within each group. In practice, it is hard for groups to achieve exact balance. Groups may be influenced by a number of factors and the individual style of group members. One indicator of group symmetry is the *Gini index* (Harris et al., 2009). This is a measure of dispersion that represents the inequality among values in a frequency distribution with a single number between 0 and 1, where 0 is perfect symmetry and 1 total inequality.

Figure 8-12 shows the extent to which physical participation (meaningful touches on the surface) and contribution (parts of the final product added by each student) were equally distributed among group members. On *equality of participation* in *Activity 1* (A1), more than half of the groups (26 groups out of 40) had high levels of equality (Gini index  $\leq 0.4$ ). But in *Activity 2* this equality dropped to only 15 out of 40 groups. This difference was statistically significant ( $t(47) = 2.71$ ,  $p < .0094$ ) indicating physical activity on the table was more egalitarian in *Activity 1* than in *Activity 2*. After looking at these results, the teacher commented that in *Activity 1* “everyone starts with the same basis so at the beginning they don't know who's the leader, who understood the case ... I am not surprised that groups tended to be equal in activity one”. This difference can also be explained by the nature of *Activity 1*. This consisted of building the organisational structure, working in a group, and drawing on each individual's preparation for the class. For *Activity 2*, it was observed that there was typically more oral discussion, since team members had already reached a consensus on the concept map and were aware of its structure. The few new actions were typically performed by the *spokesperson* or *delegate* in the team.

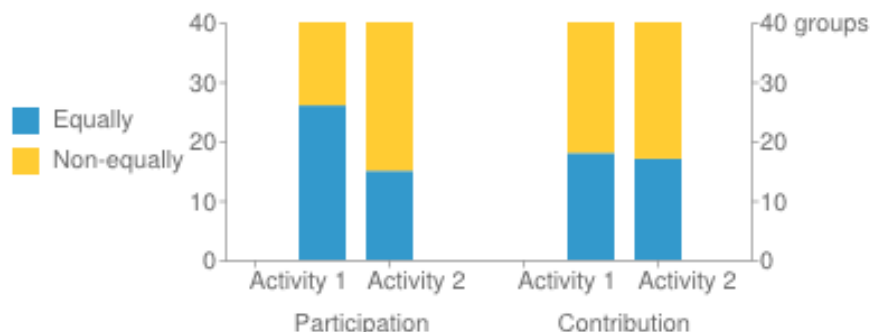


Figure 8-12 Groups according to their equality of physical participation and contribution for activities 1 and 2.

For the goal of *equality of contribution* (A2), we observed a different situation. The contributions to the product of *Activity 2* only included the portion of actions that changed the previous map from its state at the end of *Activity 1*. The number of groups with high *equality of*



*contribution* for both *Activities 1 and 2* (Gini index < 0.4) was 18 and 17 out of 40 respectively. A deeper analysis of both *participation and contribution* showed that groups where students participated more equally also tended to produce final products with parts added by all group members (Corr. 0.509). These results can be useful for the teacher to have an overall view of group's equality. The teacher commented that, for further tutorials, *"this is an interesting result,... [next time] I should emphasise and make sure that everyone is fine to use the tabletop and include their ideas to minimise the non equality aspect"*. However, other group's strategies can also be valid. We observed during the tutorials that some groups agreed that they all were going to discuss the topic and only one student would perform the physical actions. This brings up the limitation of what can currently be captured by the tabletop and what cannot.

#### *Adherence to the class script*

The teacher's intention of the design was that both activities associated with the use of the tabletops would take similar time, allowing the teacher to explain and encourage reflection between and after these (Table 8-1, rows B1, B2). Multiple factors can affect the time actually taken by the teacher to move from one phase to the other, even when tabletops can help to coordinate the enactment of the script. For example, different groups may work at different rates, some students arrive late, ask the teacher more questions, or the teacher can just take more time explaining key points (Dillenbourg et al., 2011). Timing differences can have serious effects on student's learning experiences, especially if key phases need to be skipped when the class ends and students must leave. Interactive tabletops, orchestrated through our system, can help teachers monitor the actual enactment and assess whether the script was followed in the classroom.

Figure 8-13 shows the planned script for the learning activities (upper line): 10 minutes (') for initial explanations, 15' for each tabletop activity (blue lines), and 5' for each reflection phase, between and after the tabletop activities. Results over the 14 class sessions are shown underneath. For the initial explanation, the teacher took slightly longer than planned (mean of 11', against planned 10'). *Activity 1* and the reflection before *Activity 2* matched closely with the design (mean of 15' and 5' respectively). However, the time for *Activity 2* was shortened in most of the sessions to 11'. This partly caught up time from the initial explanation and also gave a little time for students to share and reflect about what they did in the classroom (7') forcing the teacher to use more time than the 50 minutes allowed. This had an impact on the learning experience, as explained by the teacher: *"Even when Activity 2 was the most interesting from a learning perspective, I couldn't make Activity 1 shorter because Activity 2 depended on what they did in Activity 1."* This may be acceptable for the teacher if time initially allocated for *Activity 2* (11' instead of 15') still allowed enough time for students to complete the task. If this information is available after the first classes of the week, the teacher could revise the design for future tutorials or for other tutors. The teacher suggested a possible re-design of the tutorials script: *"This is a very good reminder... maybe the structure for the next tutorials should be changed to give more time for Activity 2"*.

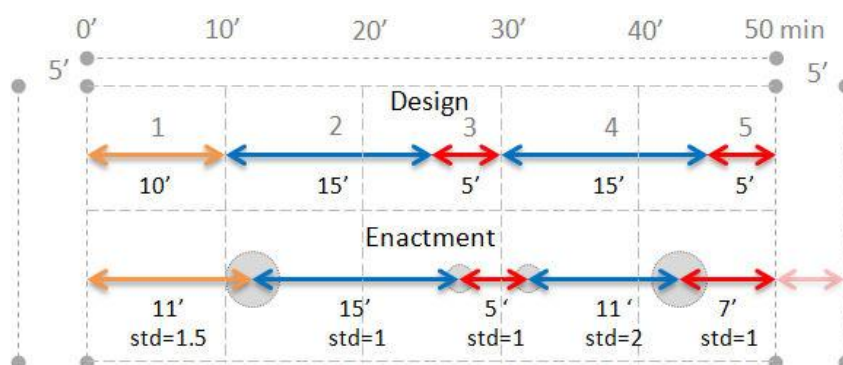


Figure 8-13 Comparison between the planned time limits and the enactment of the design for the 14 tutorials.

Another potential group issue that can be detected from the student's application logs is whether the time allocated for the activities was enough for the students to complete the goal (Table 8-1, Row B3). Figure 8-14 (left) shows the relationship between time (average time for *Activity*

1 = 15 minutes,  $SD=1.3$ ) and the number of links (or propositions) created by the 40 groups for *Activity 1*. Most groups started creating links by minute 5, and finished with an average of 20 links in their maps. The teacher had expected that all groups would get started much faster than they did since there was no previous experience with this concept mapping activity in the classroom. Figure 8-14 (right) shows the *time versus number of links*, comparing high achieving groups with low achieving groups.

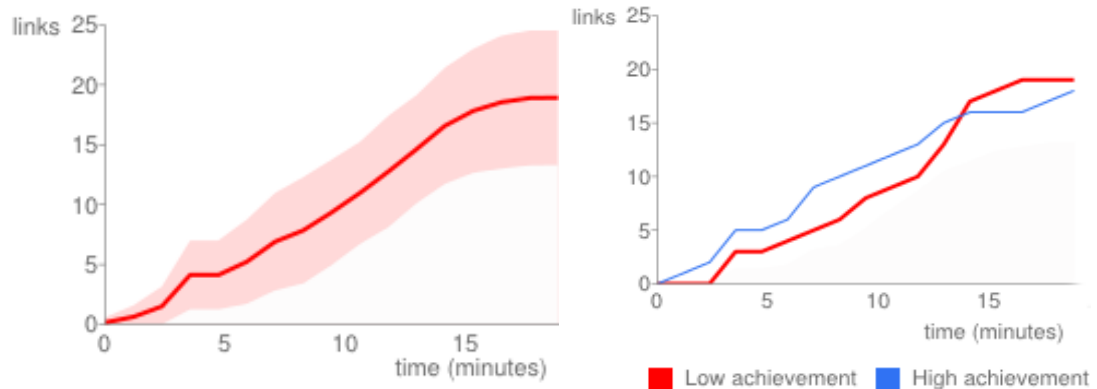


Figure 8-14 Left: Relationship between time and number of links created by the 40 groups for Activity 1. The shaded area represents the standard deviation. Right: Relationship between time and number of links created comparing high and low achieving groups.

For measuring the level of achievement, each student map was assessed by counting the number of propositions matching the teacher's master list of crucial propositions for *Activity 1*. Groups were rated high achieving if they had more than 50% of these crucial propositions. This analysis suggests the low achieving groups took longer to get started. The high achieving groups started to create links in minute 1 and kept adding them at a constant pace (blue line in Figure 8-14, right). By contrast, low achievers only started creating links in minute 3 on average. This gives a weak statistical difference ( $t(16) = 1.8, p < .087$ ). The teacher responded that, even when it may be possible to find some trend between groups that start building the solution late and their low final outcome, it is not possible to generalise the cases. *"It would be more valuable to get this information per each group during the tutorials"*. A striking feature of these graphs is that the rate of creation of propositions appears to be rather steady over the first 15 minutes, the time allowed in the design. This is valuable information for the teacher's reflection on their design, even if the time constraints of the class make it challenging to make big changes on the original plan.

#### *Learning outcomes for activities 1 and 2*

The goal of *Activity 1* was that groups should *identify the key concepts* of the topic and *their relationships or links* (Table 8-1, row C1). At the same time groups should not have *irrelevant concepts*. To measure this, each group map was compared with the teacher's map. This listed the concepts and links that the teacher considered crucial to solve the case. Results showed that the 40 groups added an average of 50% of teacher's concepts ( $SD=.15$ ), meaning they missed half. In terms of essential links, 60% ( $SD=.30$ ) of group map's links matched with the master map's. The number of *non relevant concepts* added was also high. The 60% ( $SD=11$ ) of the concepts students added were not essential concepts. Without expert analysis, we cannot conclude that these were not relevant. But in the words of the teacher, *"this indicates a lack of knowledge from some students. More training is needed for students to understand how to differentiate what is important from what is not in a case"*. This suggests the potential value of a new functionality that would provide the teacher, in *real-time*, overview comparisons of *desired* and *actual* maps. This information may enable the teacher to react and adapt the strategies used in the activity. For example, in this case, the teacher mentioned that *"one possible strategy to make them look at the case more carefully would be to have a sort of punishment for including non relevant information"*.

Also in *Activity 1*, groups should have represented the power distribution of the key concepts by choosing a hierarchical reference between two options suggested by the teacher: concentric or



linear/top-down (Table 8-1, row C2). This means that the player within the company with the highest level of power (the CEO in the case study) should be placed either in the centre or at one of the sides of the tabletop. The analysis showed that 18 groups chose the concentric hierarchy, 16 a linear one, and 4 did not show any hierarchical arrangement. Figure 8-15 shows examples of a concentric hierarchy (*left*), and a top-down hierarchy (*right*). From a learning perspective, both types of hierarchy can correctly represent the levels of power. Results showed that groups that chose the concentric arrangement were partly correlated (Corr 0.4) with higher levels of equity of participation (low Gini factor). This was informative for the teacher to re-design future tutorials, and it was expressed as: “now that I know there is some relation between layout and participation, next time I would ask students to use a circular layout”.

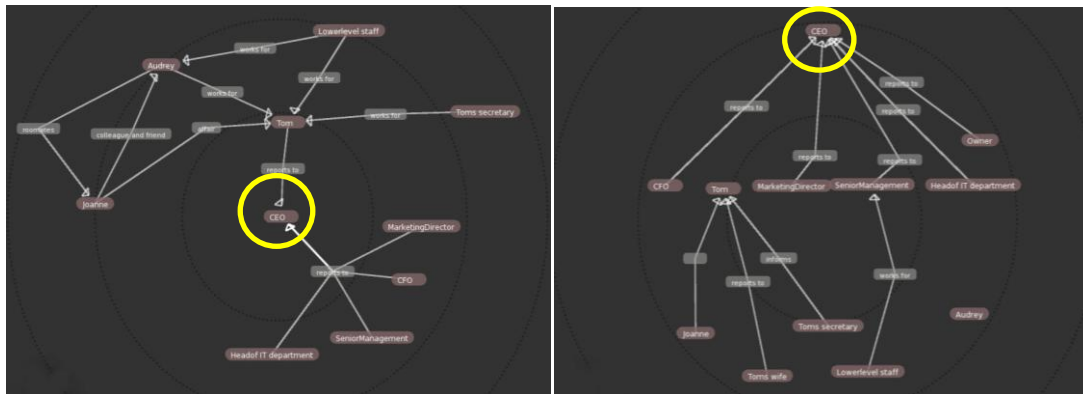


Figure 8-15 Concept map's common layout arrangements. Left: Concentric map arrangement. Right: Linear map arrangement. The yellow circle indicates the most general concept.

### 8.4.3. Section Summary

Interactive tabletops offer new affordances for collaborative learning activities. This first study presents the first published *authentic* case of a multi-tabletop system and the automatic data analysis that can help reveal some challenges for *classroom orchestration* in a multi-tabletop classroom. The main goal was to exploit the affordances of these devices to assess the teacher's design and promote reflection on the design and its enactment by analysing activity data captured during the classroom enactment. This work serves as a foundation for conducting richer analyses of data that draw upon different sources, more devices and tools involved in the classroom, with multiple sessions, and combinations of physical and virtual interactions. The section presents a second set of tutorials that resulted from the activity re-design, assisted by the results described in this section. These second tutorials are focused on delivering visual representations, of information about each group's performance, for the teacher, and other orchestration tools, to lead class reflection. In the next sections we also explore the rich data that can be collected, to analyse the collaborative interactions and look for patterns associated with high or low achieving groups, so that these can drive alerts to the teacher in *real-time*, about potential problems in the classroom.

## 8.5. Classroom Activity Design (Tutorials 2)

This section, and the studies that will be described in Section 8.6 and 8.7, focus on the second set of classroom sessions. This had 8 tutorials, run in the 6<sup>th</sup> week of Semester 2, 2012, for a course titled “Management and Organisational Ethics” of the University of Sydney. In total, 140 students attended these tutorials. These were conducted by the same teacher as in the first study. Each tutorial session had 15 to 20 students. The teacher arbitrarily formed four groups, with 4 or 5 students at each table. All students knew each other. As in the first set of tutorials, the teacher designed a case-resolution activity to cover the set topic as defined in the curriculum for that week. Even though the subject and topic for this tutorial were different from the ones in the first set of tutorials, a similar macro-script was defined by the teacher (see Appendix Section A.4.8). The class time was also fixed at 50

minutes. The objective for this activity was a case-resolution problem in the context of organisational ethics (see Appendix Section A.4.5). There were key differences in this second set of tutorials as a result of the reflection for re-design that was triggered by first study. These differences are outlined in Table 8-2.

The re-designed macro-script for these tutorials is described as follows:

1) *Introduction* (10 minutes): the teacher forms groups, explains the tutorial objective, shows students how to use the concept mapping application and explains the objectives of the first activity.

2) *Activity 1* (10 minutes): the teacher uses the MTDashboard to ensure that all groups *start* at the same time. The four tabletops respond by clearing the interface and loading a small *scaffolding concept map* (5 concepts and 2 links set by the teacher, see Appendix Section A.4.9). Students have to complete this map showing how the main actors of the case are linked. The main difference with respect to the macro-script of the previous tutorials is the impact of the pre-loaded map. The teacher explained that this serves two purposes: to help students to build their initial map by focusing on the creation of the key links between the concepts of their map; and encouraging students to follow a concentric layout of their map since it was previously found that there is a correlation between this type of layout and a more egalitarian participation of the group members.

3) *Reflection 1* (5 minutes): the teacher *blocks* the tabletops and introduces Activity 2, explaining it and leading class discussion about possible solutions to the case.

4) *Activity 2* (15 minutes): for the teacher, this is “*the most important activity of the tutorial from the learning perspective*”. The teacher *unblocks* the tabletops; and students discuss the task and complete their concept map. There should be more time allocated to this activity compared to the previous design.

5) *Group sharing and final reflection* (10 minutes): the teacher *blocks* the tabletops again and then asks each group to share their solution with the class. The teacher uses the function *send to the wall* for each table in turn. After each group has explained their concept map, the teacher summarises the outcomes of the activity and finishes the session.

Table 8-2 Main differences between tutorials organised in semesters 1 and 2, 2012.

Set of tutorials	Tutorials Set for Semester 1	Tutorials Set for Semester 2
Number of sessions	14	8
Total participants	236	140
Topic	Organisational politics	Ethics in the workplace
MTDashboard	Laptop device	Handheld device
- Script-control options	Yes	Yes
- Visualisations	No	Yes
- Broadcast message	No	Yes
- Send individual maps to the wall display	No	Yes
Activity 1	Creating a structural map from scratch	An <i>initial scaffolding map</i> is provided. This is result of the re-designed informed by the results described in Section 8.4.
Activity 2	Complete the concept map representing a solution for the case.	More time was allowed to students to complete their map.
Layout Instructions	Students were suggested to arrange their concept map following a concentric or linear hierarchy.	Students were encouraged to arrange their map in a <i>concentric layout</i> following the arrangement of the preloaded key concepts (5).

The next sections describe two studies. The first one evaluates the affordances of the MTClassroom for providing *real-time* support to enhance teacher’s awareness and control in the classroom. The second study consists in analysing key differences between groups to discover strategies that can help understand how groups collaborate according to their level of achievement.

## 8.6. Supporting Teacher's Awareness and Control

In this section we investigate the affordances of our environment for classroom control and the impact of the information provided to the teacher through the MTDashboard. For this, we make available for the teacher visual representations of group indicators, their design and validation were presented in Chapter 6.

### 8.6.1. Study Description

Two different conditions of the MTDashboard were used across the 8 tutorial sessions. For Condition 1, the dashboard (Figure 8-16) included the *Group Map Visualisation* that represented the size and distance of each map from the teacher's map (Figure 8-16, right – condition 1, and Figure 8-17, left). This information was explicitly requested by the teacher because she wanted this concept map quality measure that is not normally available during the limited classroom time. The second version of the dashboard presented the visualisation *Radar of Physical Participation* that shows the number of touches on the tabletop per student and the equality among group member (Figure 8-16, right – condition 2, and Figure 8-17, right). The design of this visualisation was suggested by the teacher in the previous tutorials (Semester 1). She commented that “*quantitative information about student's actions would be useful for identifying participation*”. This visualisation was inspired by previous work on group chat communication. A larger range of visualisations (some more elaborated) were offered to the teacher (refer to Section 6.4.3), but she did not selected them for this study.

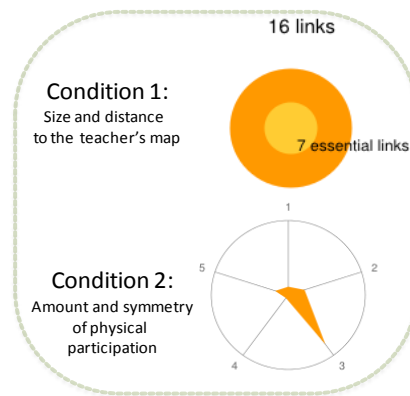


Figure 8-16 Left: A teacher attending a group while holding the MTDashboard. Right: The two visualisation conditions.

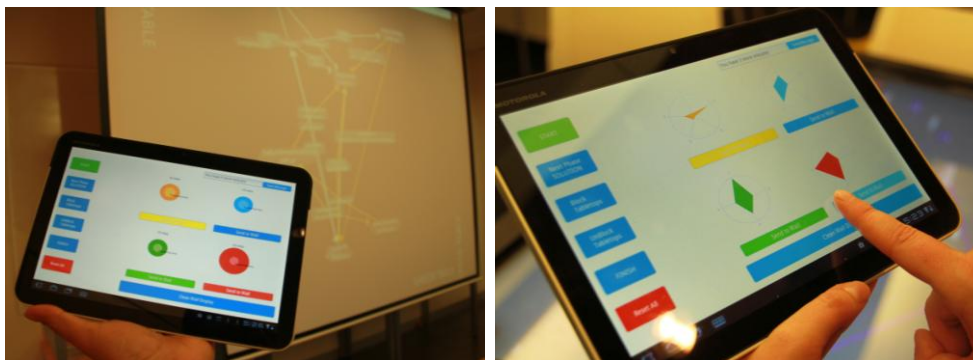


Figure 8-17 MTDashboard: condition 1 (Left), and condition 2 (Right).

**Research questions.** When teachers orchestrate multiple groups in the classroom, one of their challenges is to identify the group that most needs immediate attention (Dillenbourg et al., 2011) whilst, concurrently, spending a relatively balanced amount of time with each group, to be fair to all students. This is where MTDashboard can provide awareness support for the teacher, enabling an informed decision about which group to attend to next. For this, we sought to address the next questions: *What is the impact of the information provided to the teacher by the MTDashboard during*

*the classroom sessions? Is the teacher attending to the “lower achieving” groups, according to the information provided?*

#### *Data collection.*

We collected information from a number of sources to triangulate evidence. These sources included: automated capture of the MTClassroom, notes from an external observer focused on teacher’s actions, notes from a second external observer focused on assessing each small group’s work and notes from interviewing the teacher. The *automatically captured data* consisted of synchronised logs of the host application at each tabletop (differentiated student’s actions and partial states of the concept maps), logs of teacher’s actions using the MTDashboard, and partial distances of group artefacts from the teacher map (see Appendix Section A.4.7). The *manually captured quantitative/qualitative data* consisted of the observed time and duration of the moments when the teacher: i) *attended to or intervened* with a group, ii) looked at the MTDashboard, iii) spoke to the whole group, iv) walked around the class or did not look at any specific group. These observations were captured through a console synchronised with the application logs. The second set of observations consisted of quantitative assessments of perceived qualitative collaboration per group based on an adapted rating scheme (Meier et al., 2007), similarly to the study presented in Section 7.2.4. Our modified scheme has 4 dimensions of collaboration, quantified from -2 to 2, for each of (a) mutual understanding and dialogue management, (b) information pooling and consensus (c) task division, time management and technical coordination, and (d) reciprocity. This is the same scheme used in the studies presented in Chapter 7 but simplified to allow a single observer to collect qualitative information from multiple groups in the classroom. This assessment is not exhaustive but served to gain secondary awareness of each group’s level of collaboration since the teacher also assessed groups at the end of each tutorial, using one of three possible values: low, medium or high achieving. Finally, we conducted semi-structured post-tutorial interviews with the teacher to obtain feedback on the functions and visualisations provided for *classroom orchestration*.

#### *Data exploration.*

To analyse the teacher’s attention distribution, we first define the terms *attention* and *intervention*. We consider that a teacher pays *attention* to a group when their gaze is focused on or they interact with that group. *Intervention* is the *subset* of such *attention* that happens only when the teacher interacts with the group, therefore interrupting their work. We made this distinction based on our previous study in which the teacher stated that for some outstanding groups they would “*see what they are doing*” but mostly leave them work by themselves (Section 6.4.6). During the post-tutorial interviews the teacher commented that she “*tried to provide equal attention to all groups*”, while “*focusing on groups that needed more help*”. This means that the teacher dynamically chose the order in which she attended to each group. Having made this distinction, we now describe an example of the teacher’s actions at the MTClassroom.

Figure 8-18 shows a transition diagram where the nodes represent the elements that were at the focus of teacher’s attention. The nodes correspond to *each group*, the *MTDashboard* or the whole *Class*. The latter includes the times when the teacher was not attending to any particular group or gave a message to the whole class. The directed arrows between the nodes represent the transitions recorded by the external observer (45 transitions registered in this example).

In the group shown in Figure 8-18, the teacher devoted most time to the *red* group (32% of attention and 29% of intervention time) compared with the others (20/8%, 26/16%, and 21/10% for *green*, *yellow* and *blue* tables). In fact, the teacher assessed the *red* group as the only *low achieving* group in the class, therefore confirming that the attention in this class was not equally distributed. We also observed that the teacher never attended to the *green* group after looking at the dashboard (there is no transition line from *Dashboard* to *Green* node). Coincidentally, the green group also received the fewest interventions. This motivated the analysis of the rest of the cases to find evidence that confirms the impact of the information delivered through the dashboard on teacher’s attention. In other sessions, the accumulated attention was more egalitarian. An analysis of dispersion of *attention* and *intervention* among the sessions showed that the teacher paid attention to all groups largely equally (mean index of dispersion, Gini factor, for attention= 0.12 and

intervention = 0.124, where zero means perfect equality). The next section describes our evaluation of the impact of the nature of the information displayed through the dashboard on teacher attention and intervention. The actions that the teacher took after looking at the MTDashboard are the focus of our evaluation (thicker transition lines in Figure 8-18).

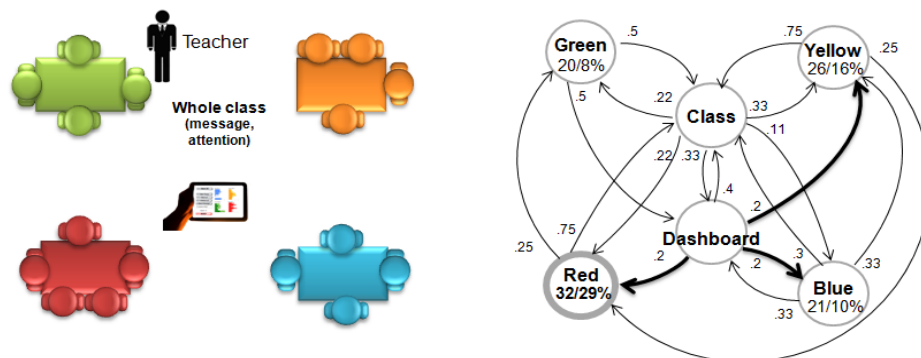


Figure 8-18 An illustrative transition diagram of the process of teacher's attention in one classroom session.

## 8.6.2. Analysis and Discussion

This section is divided into three parts. The first two tackle our research questions and the last one explores the impact of teacher's feedback about students to complete our analysis of the orchestration loop at our environment.

*Analysis, part 1: What is the impact of the information we provided to the teacher?*

For the first question (*What is the impact of the information we provided to the teacher in real-time, during the classroom sessions?*), we started by analysing whether there was any relation between the observed *performance* of each of the 32 groups during the tutorials with the accumulated amount of time that the teacher dedicated to attend or intervene each of them. We divided the groups according to the two conditions of the information that was provided to the teacher through the MTDashboard. The two conditions were: (i) distance from teacher's map and (ii) *physical participation* (see Figure 8-16).

We performed correlation analyses between *attention/intervention* and group *performance* measured in different levels and from different sources: the external observer that measured collaboration, the artefact that students built and the teacher assessment. Table 8-3 shows the results of these analyses, where *Attention time* and *Intervention time* are the proportions of the time the teacher dedicated to inspect and interact, or just interact, with specific groups respectively. Regarding the columns of group's performance, columns *ob1*, *ob2*, *ob3* and *ob4* correspond the 4 categories used by the external observer to assess group's collaboration according to the schema adapted from Meier et al. (2007). Column *Obc* corresponds to the correlations with the cumulative score of these 4. Columns *Size map* and *Dist* correspond to the correlations with, respectively, the size and the distance of group's map from the teacher's map. Finally, the column *Tchr* indicates the correlations with the quality of each group as assessed by the teacher.

Table 8-3 Correlation analyses between Attention/Intervention and Group's performance.

i) Distance to teacher's map																	ii) Physical participation									
Group's performance	►	Observed collaboration					Size map	Dist	Tchr	Observed collaboration					Size map	Dist	Tchr									
	ob1	ob2	ob3	ob4	Obc					ob1	ob2	ob3	ob4	Obc												
Attention time (%)	-0.20	0.33	0.34	-0.10	0.44	0.29	-0.30	-0.10	-0.26	-0.10	-0.33	-0.32	-0.30	-0.10	0.48	0.00										
Intervention time ( %)	-0.10	0.37	0.34	0.02	0.45	0.34	-0.16	0.02	-0.20	0.05	-0.32	-0.38	-0.27	0.03	0.34	0.15										
Correlation	low -	med/ low +	med/ low +	no	p<=0.1	med/ low +	low -	no	low-	No	med/ low -	med/ low -	med -	no	p<=0.1	no										

Results showed a difference between the two conditions for the correlation between *observed collaboration* and *attention/intervention time*. For condition (i) distance from teacher's map, we

found a significant positive correlation between levels of collaboration and the attention and intervention provided by the teacher (columns *ob2*, *ob3* and *Obc*, left). On the other hand, for condition (ii) *physical participation*, we found a negative moderate correlation (columns *ob1*, *ob3*, *ob4* and *Obc*, right). From a teaching perspective, a negative correlation might appear desirable, since it would mean that the teacher provided more attention to the low groups. However, a perfect correlation is unrealistic, since the teacher cannot totally neglect high achieving students and, indeed, the teacher had the goal of giving some attention to each group. To explain these findings, we triangulated this evidence with the teacher's statements during the post-tutorial interviews. The teacher found that the information provided in condition (i) was useful during the class and it was expressed as: "*I looked at the number of relevant links because one group could have 21 links, but how many of them actually matched my map? For a group with 9 linkages with most of them matching my map, I would be satisfied*". This means that information about the distance to teacher's map in condition (i) helped the teacher recognise the groups that might have needed more help. The analysis supports this since the only negative correlation of condition (i) was for column *Dist* (-0.3 and -0.16 for attention and intervention). The level of collaboration of groups does not determine the qualitative aspects of their artefacts; therefore there were no negative correlations for *observed collaboration* in condition (i).

For condition (ii), the teacher stated that the information provided by the *Radars of participation* was good but was not used much because "*a lot of the times groups decided that one only person was going to do the links or I [the teacher] could tell by looking at the table that everyone was discussing but only two or three people were actually moving things around. Then, by looking at the diagrams only, I couldn't interpret [them] as the group was not working*". Therefore, during these tutorials for the second condition, the teacher mostly used what she could observe and hear from each group. We argue that this is the reason why the attention and intervention are more aligned to the *observed* level of collaboration (negative correlations for columns *ob1*, *ob3*, *ob4*, *Obs* in condition *Physical participation*). As the information about the size of the map and the distance to the teacher's map was not provided in this condition, we found no correlation or positive correlation respectively (columns *Size map* and *Dist*). Finally, the teacher's assessment seemed independent from her decisions to provide attention (values are close to zero in *Tchr* columns for both conditions). The teacher explained that the group's assessment was primarily based on the explanations that each presented to the class towards the end of the tutorial, and also influenced by the student's conversations that she could overhear and the group's indicators of distance to teacher's map provided in condition (i). Therefore, the teacher's assessment was not connected to her evaluation of which groups needed the most help at some point. This suggests that, while the cumulative analysis (*part 1*) is informative in both conditions, we also need to conduct further analysis taking into account the times when attention was provided to groups.

#### *Analysis, part 2: Is the teacher attending the 'less achieving' groups?*

As group's needs for teacher attention vary in time, the teacher needs to continuously monitor group's performance to try and keep the levels across groups as close as possible. Here is where our second research question arises: *is the teacher attending the 'less achieving' groups according to the information provided?* To answer this, we analysed the decisions made by the teacher right after looking at the dashboard. There were 38 teacher's actions that were captured by the external observer and synchronised with the MTClassroom's logs (17 for distance from teacher's map and 21 for *physical participation* conditions).

*Condition (i).* For each time when the teacher looked at the dashboard, and for each group in the classroom, we calculated the quantitative indicators of size and distance of the map provided by the *Group map visualisation* at that moment. Then, the groups were ranked from the smallest and furthest map from the teacher's map to the biggest and closest map at that point in time. There were 3 possible ranks: *furthest behind* group(s), the *strongest* group(s), and the groups in between. The strongest group at a determined moment was the one with more crucial links and less irrelevant links according to the teacher's map. Then, we identified the group that the teacher chose to attend to next. After this, we assessed the category of the group chosen by the teacher, for example, if the teacher chose the furthest behind group or a strong one.

Table 8-4 Analysis the groups that the teacher attended to for condition (i) distance to teacher's map.

Condition: distance to teacher's map	A) Map information was Provided	B) No information about the map was provided
Total	17	21
	Proportion %	Proportion %
Less achieving	5	4
Not the best groups	9	8
The best group	3	9

Table 8-4 shows the results of this analysis. Column A corresponds to the 17 cases of teacher's attention after inspecting the dashboard of the condition under analysis (i). Column B corresponds to the other cases where the second type of information was provided (ii). We found that when the map size and distance to the teacher's map information was provided (column A) the teacher only decided to attend the strongest group 18% of the times (3 out of 17 cases). By contrast, when this information was not provided, the teacher attended to the strongest group 43% of the times (9 out of 21). This confirms that showing information about each group's artefact in 'real-time' had some impact on the teacher's decision as to which group to attend to next. It also validates what the teacher had stated that looking at the number of relevant links added by each group give her a better idea of the group's performance.

*Condition (ii).* We calculated the information provided by the visualisation *radar of physical participation* for the 38 cases when the teacher looked at the dashboard. We had the same 3 possible ranks. In this case, the strongest group was the most equal in terms of participation. We measured the rank using an index of dispersion, the Gini coefficient. This is a number between zero and 1, where zero means perfect equality of student's participation. We followed the same process as the previous condition. Results are shown in Table 8-5. These confirm that the participation radar, at least in the way in which we presented it, did not provide information to influence the teacher to take decisions about which group to attend to next. The teacher decided to attend to low or high achieving groups at almost the same extent (33%, 38% and 28% of the times). The post-tutorials interview confirmed that the teacher did not use the information about physical participation, justifying this with the argument that "*not everyone was touching the tabletop but they were speaking a lot and this is good from a learning perspective*". The teacher also argued that this information "*would be very helpful in a bigger class*". The teacher described this as follows: "*I cannot observe 80 people but I can observe 20 people, I could tell who was talking. It would be fantastic to check the participation information for a bigger group*".

Table 8-5 Analysis the groups that the teacher attended for condition (i) physical participation.

Condition: physical participation	A) No information about participation was provided	B) Participation condition
Total	17	21
	Proportion %	Proportion %
Less achieving	4	7
Not the best groups	9	8
The best group	4	6

### Analysis, part 3: Did teacher's interventions have an impact on student's performance?

Finally, we investigated whether the teacher's intervention actually had an impact on student's performance immediately afterwards. We considered as indicator of performance the number of relevant links created by each group. The teacher intervened in groups a total of 74 times in the 8 classroom sessions. For each intervention, each group was ranked at the moment the teacher started the intervention from 1 to 4 (from low to high group, according to the teacher's map distance of the four groups in the class). Then, we assessed if there was an improvement (or decrease) of the map 2, 3, 4 and 5 minutes later (interventions lasted up to 2 minutes and each activity lasted from 8 to 10 minutes). For example, at minute 5:05 the teacher attends to the Green group. At that exact moment, this group had the furthest map to the teacher map in the class, so their rank was 1. We divided the 74 interventions in two groups according to the 2 conditions of the information provided.



Table 8-6 Analysis of the Impact of teacher's interventions: correlation analysis between the rank of a group among the others in the classroom and the improvement of their artefact's distance to the teacher's map.

Condition	# interventions	after 2 min	after 3 min	after 4 min	after 5 min	
Distance to teacher's map	40	-0.4, $p \leq 0.01$	-0.27, $p \leq 0.05$	-0.32, $p < 0.025$	-0.27, $p \leq 0.05$	Significant correlations
Physical participation	34	0.08	-0.05	-0.05	-0.02	No correlation

Results of the analyses of correlations between the rank of each attended group and the improvement of the teacher's map distance are shown in Table 8-6. For condition (i), Distance from teacher's map, we found significant negative correlations. This means that the groups that were lagging significantly improved their teacher's map distance after teacher's intervention. However no correlation was found in condition, (ii). We can therefore argue that the teacher's intervention had a significant impact on the group's artefact when the information about the distance to the teacher's map was provided. This once again provides evidence that supports the benefits of showing information about the quality of student's work to the teacher in *real-time*.

Our analysis completed the circle of teacher's orchestration that includes: *awareness, intervention and student's action* following this intervention. We found some trends by analysing the accumulated attention and intervention by the end of the tutorials. Then, we obtained stronger evidence confirming the importance of showing indicators of quality of student's work to drive teacher's decisions. Finally, we found that *informed* interventions of the teacher can lead students to improve their solutions from to teacher's perspective.

### 8.6.3. Section Summary

The contribution of the second study, presented in this section, is the novel approach for providing teachers with key indicators of small group collaboration in the classroom and analysing their impact on teacher's attention to help them manage their time more effectively. We confirmed that the data presented to the teacher in the classroom can drive their focus of attention especially when information about the *quality* of students work is delivered. The teacher described this as follows: "*I think the dashboard was really good, especially because it showed things about the quality of their work. If I haven't had this information about the relevant links then I had to look at the whole diagram so it would take longer to look at each map*". Our study also confirms that the teacher would value indicators of group work and individual participation for post-hoc analysis. The teacher commented: "*I don't want to see a lot of information in the dashboard, this can be distracting. But more information can be provided after the tutorials for assessment wise, like who did what, when, and the quality of the work*". The work presented in the next section includes a detailed analysis of the student's information using data mining and process modelling techniques to extract patterns of interaction that aim to provide more insightful indicators for teachers after the classroom sessions.

## 8.7. Mining Student's Actions

The teacher in the classroom can face a number of challenges related with control, awareness and resources management (Zhang et al., 2004). These depend on a number of factors that may fall out of the scope of what tabletop systems can capture. The tabletop systems are not fully aware of the classroom situation, for example, if a group of students is talking, if they work on-task or if someone needs to leave the class. As discussed earlier, the teacher may have a better idea of the productivity of student's discussions within each group. However, one of the main conclusions after finishing the first set of tutorials was that for the teacher it is not easy to know aspects of the final artefacts that students built, their individual contributions or the process they followed. In a post-tutorial interview the teacher expressed her views as follows: "*I don't want to see a lot of information in the dashboard, this can be distracting. But more information can be provided after the tutorials for assessment, like who did what, when, and the quality of the work*". These are indeed the aspects of

group work that tabletops are aware of in detail. The MTClassroom can capture: 1) differentiated student's actions on the tabletop; and 2) the sequence of these actions.

Inspired by the above teacher needs, but framed in what tabletops can actually capture in an authentic classroom, we propose an approach to distinguish strategies followed by groups that either needed more coaching or worked effectively. We analyse three sources of contextual information i) identified individual actions on the tabletop that can occur in parallel, in turn, or on other student's objects, ii) the quality of student's actions according to the teacher's artefact, and iii) the impact of student's actions on the group artefact. In this section we focus on the student's actions performed in Activity 1. This is important because a certain level of success in Activity 1 is required for Activity 2. This also makes the approach applicable in *real-time*, to provide feedback to teachers before the tutorial is over, so they can target their support during Activity 2.

The contributions of this section are: i) an approach to mine face-to-face collaboration data unobtrusively captured at a classroom with the use of multi-touch tabletops, and ii) the implementation of sequence mining and process modelling techniques to analyse the strategies followed by groups of students. The results of this study can be used to provide *real-time* or after-class indicators to students; or to help teachers effectively support group learning in the classroom.

### 8.7.1. Study Description

The *initial raw data* of each group consists of a long sequence of actions in which each element is defined as: {*Resource*, *ActionType*, *Author*, *Owner*, *Time*, *Relevance*}, where *Resource* can be: *Conc* (concept), *Link* (proposition) or *Menu*. *ActionType* can be: *Add* (create a concept or link), *Del* (delete), *Mov* (move) links, *Chg* (edit), *Scroll*, *Open* or *Close* (a menu). *Author* is the learner who performed the action, *Owner* is the learner who created an object or owns a menu, *Time* is the timestamp when the action occurred and *Relevance* indicates if the concept or link belongs to the crucial elements of the teacher's map. Table 8-7 lists all the possible actions in the dataset grouped by their impact on the group concept map. Some examples of actions are: {ConceptA, Add, 3, 3, 17:30:02, Crucial}, when a learner adds a concept to the map, that also appears in the teacher's map; {LinkY, Move, 2, 6, 17:30:04, Irr}, when s/he moves a link created by another learner and that does not appear in the teacher's map; and {MenuConcepts, Open, 2, 2, 17:30:07, -} when s/he opens the list of suggested concepts. The original sequence obtained for each group contained from 74 to 377 *physical actions*.

Table 8-7 Possible actions on the concept mapping tabletop system

High impact actions (content and structure)	Low impact actions (layout)	No impact actions
Add a concept/link	Move a concept/link	Open or close menus
Delete a concept/link	Merge two links	Move/scroll menu-concepts
Edit a concept/link		

The teacher assessed groups at the end of each tutorial, using one of three possible values: low, medium or high achievement. The teacher specified that the assessment criteria mostly considered the *quality of each group solution* presented at the end of the tutorial and the *quality of their discussions* during the tutorial. We considered the activity data of all the 32 groups divided in two sets: 20 groups that were high achieving and 12 groups that were medium or low achieving.

We address four questions regarding the strategies and characteristics that can differentiate groups according to their extent of achievement. The formulation of these is based on the triangulation of the available data (differentiated student's actions and their impact on their artefact), the teacher's needs (awareness of student's participation and quality of their work), and open issues in the study of multi-tabletop classrooms. Our research questions are:

1) *Can we distinguish groups by inspecting patterns of parallelism and concurrency?* As the teacher is interested in the participation of all students in the construction of the group solution [10], we analyse whether it is possible to find differences between groups where students worked at the same time or not. We differentiate actions performed by different students at the same time

(actions in *parallel*) from the actions by different students performed in sequence one after the other (*concurrent* actions).

2) *Can we distinguish groups by inspecting student's interactions on other's objects?* Other studies inspired this question; these have suggested that interacting with what other's have done may trigger further discussion that is beneficial for tabletop collaboration (Fleck et al., 2009).

3) *Can we distinguish groups by inspecting student's map quality?* This and the next question are directly motivated by teacher's needs, as noted above, and the data captured by our system about the group's artefacts and the process followed to build them.

4) *Can we distinguish groups by inspecting the process followed by student's actions and their impact on the group artefact?*

## 8.7.2. Methods: Sequence Mining and Process Mining

Sequential mining and process mining are techniques that have been used to identify patterns in educational datasets by considering the order of student's actions (Kinnebrew and Biswas, 2012; Martinez-Maldonado et al., 2011f; Pechenizkiy et al., 2009). We used a sequential pattern mining technique called *differential sequence mining* (Kinnebrew and Biswas, 2012) to distinguish strategies followed by groups that were either high or low achievers. For the sequential mining, we analyse two of the sources of contextual information listed in the previous section: i) identified actions on the tabletop and ii) the quality of students artefact. In order to analyse the strategies that distinguish groups according to iii) the impact of student's actions on the group map, we used the *Fuzzy Miner* tool (Günther and Aalst, 2007). In the next subsections we describe the motivation for using these tools, the data pre-processing and the implementation of each technique for our study.

### Sequence mining

One of the data mining techniques that we successfully applied to our dataset collected under controlled conditions (Chapter 7) to identify patterns that differentiate high from low achieving students is differential sequence mining (DSM) (Kinnebrew and Biswas, 2012). The DSM algorithm extracts frequent consecutive ordered sequences of actions from 2 datasets and performs an analysis of significance to obtain the patterns that differentiate them. The actions can also contain contextual information as defined by an *alphabet*. We used these alphabets to *encode* each action with a number of concatenated keywords. In this study in the classroom, each action was encoded in the format *{Resource-ActionType-Context}*. We implemented a DSM solution to investigate the differential patterns in terms of degree of parallelism, actions of students on other's objects and relevance of the links and concepts students use. We designed three alphabets, each focused on one of these sources of contextual information.

Table 8-8 Keywords included in the alphabets for the sequential pattern mining.

Resource	Action type		Alphabet 1 <i>Parallelism – concurrency</i>	Alphabet 2 <i>Actions on other's objects</i>	Alphabet 3 <i>Master map distance</i>
<i>Concept (Conc)-C</i>	<i>Add -C,L</i>	<i>Delete (Del)-C,L</i>	<i>Parallel</i>	<i>Own</i>	<i>Cruc (C,L)</i>
<i>Link -L</i>	<i>Edit (Chg) -C,L</i>	<i>Merge (Move)-L</i>	<i>Other</i>	<i>NoOwn</i>	<i>NoCruc (C,L)</i>
<i>Menu -M</i>	<i>Move -C,L,M</i>	<i>Open -M</i>	<i>Same</i>		
		<i>Close -M</i>			
<i>Inactivity block (Inact)-B</i>	<i>Short (Shrt) -B</i>	<i>Long -B</i>			

Table 8-8 presents the keywords of each alphabet. The actions encoded using any of the three alphabets should contain at least one keyword from the *Resource* column and one from the *Action-type* column. We add one keyword of the corresponding contextual information according to the Resource type. Alphabet 1 aims to model the differentiated individual actions performed on the tabletop that occur in parallel (with other student's actions, keyword: *Parallel*), in turn or sequenced

(when the previous action was performed by a different student, keyword: *Other*), or as a series of actions by the same student (*Same*). Alphabet 2 models the actions that students perform on their own objects (*Own*) or on other student's objects (*NoOwn*). Finally, Alphabet 3 indicates whether the concept or link involved in the action belongs to the crucial objects defined by the teacher (*Cruc* or *NoCruc*). We set a minimum support of 0.5 to consider a pattern as frequent and a maximum error of one to allow matching sequences with up to 1 different action, similarly to previous work on educational data exploration (Kinnebrew and Biswas, 2012).

In the previous study in the lab, we also found that it was very important to consider the periods of significative inactivity registered by the tabletop (refer to Section 7.3.5). During these periods of inactivity students may be having productive discussions, off-task talking or not working collaboratively at all. In our study, even when we do not perform speech detection, it is important to at least consider the occurrence of inactivity. To define a period of inactivity, we explored the time gap between each action performed on the tabletop. We found that time gaps between actions below one standard deviation from the mean ( $<\mu+1\sigma$ ) account for the 92% of the set. ( $\mu= 4.30$  seconds,  $\sigma= 8.62$ ,  $\mu+1\sigma=13$  seconds). This means that a period above 13 seconds without logged actions can be considered as a block of inactivity. We defined these blocks as *short* when the gap was between 13 ( $\mu+1\sigma$ ) and 22 ( $\mu+2\sigma$ ) seconds, and *long*, for gaps longer than 22 seconds ( $\mu+2\sigma$ ). We detected from 6 to 19 periods of inactivity in each group. The output of applying the DSM algorithm, using the three alphabets, consists of three sets of frequent sequential patterns that differentiate high from low achieving groups according to the teacher's assessment.

#### Process mining

The sequence mining approach presented above can extract patterns of activity that distinguishes groups; however, it does not give insights into the higher level view of the processes followed. The Fuzzy miner (Günther and Aalst, 2007) is a process discovery technique that can generate a meaningful abstraction of a general process, from multiple instances by distinguishing the activities that are important. This technique is especially suitable to mine *unstructured* processes, like the collaborative concept mapping construction in our study.

The input of this algorithm is: a series of consecutive actions, or group of actions. The result of this algorithm is a directed graph in which each node represents an action and the edges represent the transitions between these. The nodes and edges that appear in the graph should meet a *conformance threshold* based on the instances that were used to build the model. The objective of this second analysis is to discover the meaning of the higher level steps that high and low achieving groups performed to build the concept map and the impact of such actions. For this, we performed the following data preparation before applying the Fuzzy miner tool.

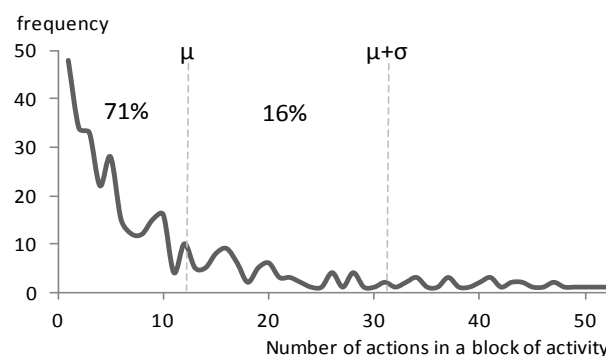


Figure 8-19 Distribution of the length of the sets of activity in terms of number of actions.

1) *Data grouping*. We grouped the actions into periods of activity in order to generalise similar actions according to their impact on the concept map. First, we explored the number of actions contained in each period of activity between periods of inactivity. Figure 8-19 illustrates the frequencies of the number of actions within blocks of activity in the dataset ( $\mu= 12.85$  actions,  $\sigma= 17.68$ ). The distribution shows a high frequency of periods with a small number of continuous actions, and a long tail of longer sets of actions. In fact, 71% of the periods of continuous activity

were below the mean size (13 actions) and the 87% of them were below one standard deviation from the mean (30 actions). We considered the mean (13 actions) as a reasonable threshold for the maximum size for a block of activity.

2) *Actions categorisation*. Based on the definition and previous research on concept mapping (Nousiainen and Koponen, 2010; Novak, 1995), we categorise student's actions according to their impact on the group map. Actions that make a change in the structure or content of the concept map are categorised as *High impact actions*. These include actions that modify the quantity or content of concepts and links (Table 8-7). The second category is *Low impact actions*, which includes actions that modify the layout of the map, that is important for the activity, but not crucial. These actions include moving concepts and links, or merging links. Finally, actions performed on the menus of the application belong to *No impact actions*.

3) *Blocks categorisation*. Each block was categorised according to the actions corresponding to that period following the next rules: *HighOnly* for blocks that contained only high impact actions and some no impact actions; *HighLow*, if the block contained at least both one high impact action and one low or no impact actions; *LowOnly*, for blocks that contained only low impact actions and some no impact actions; and *NoImpact* if the block contained just no impact actions. Periods of inactivity were categorised as either *InactShort* or *InactLong*, as explained earlier.

4) *Addition of contextual information*. We highlighted the importance of distinguishing the learners who work on their own or on other student's objects. For this, we added the information about who touched which object with the keywords *NoOwn* if most of the actions were performed on other's objects and *Own* if the actions were performed on the same learner's objects.

After performing the data preparation we divided the dataset into two sets, one for high and one for low achieving groups, as we did for the sequential mining. We generated two corresponding fuzzy models using the ProM framework<sup>1</sup>. Then, we performed two model analyses: analysis of the number of active learners, and a validation of the models to discriminate groups.

*Analysis of number of active learners*. We explore whether there is a difference in the number of learners who were actively involved in each of the significant activities that appear in each fuzzy model (the nodes of the model). For the latter, the explored values corresponded to blocks of activity in which only one learner (*1u*), two (*2u*), or more than 2 learners (*+u*) were involved in the actions within a block of activity. Taking account at the fact that that all groups had from 4 to 6 group members, it is not surprising that no correlation was found between the group size and the level of achievement of each group ( $r = 0.2$ ).

*Validation of the models*. We performed a cross validation of the two models to evaluate if they can be used to effectively differentiate high from low achieving groups. To do this, we calculate, for each group process, the level of conformance of both fuzzy models and validate that the model that fit the most corresponds to the level of achievement of the group.

### 8.7.3. Sequence Mining Results

After applying the DSM algorithm on the encoded datasets according to our three alphabets, we selected the patterns whose *instance* support (number of times the pattern is repeated within a group log) differed between the high and low achieving groups with a statistical significance of 90% confidence ( $p < 0.10$ ) and that were composed of at least 2 actions. Table 8-9 presents the top-4 most frequent sequences for each of the three alphabets explored in this part of the study.

*Alphabet 1: focused on parallelism and turn-taking*

We obtained a total of 23 *differential patterns* for groups that were either high or low achieving after analysing the first encoded dataset. The top sequences in Table 8-9 indicate the presence of actions in parallel for *move* events (sequence A) and actions that contain the keyword *Other*, when adding and moving elements of the concept map (sequences B, C and D). These provide evidence that in high achieving groups quite often more than 1 student interacted with the tabletop at the

<sup>1</sup> ProM framework: <http://www.processmining.org>

same time. In fact, the keywords *Parallel* and *Other* appeared in 13% and 66% of the frequent patterns of high groups, while in the low achieving groups there were no patterns with the keyword *Parallel* and the keyword *Other* only appeared in the 30% of them.

*Alphabet 2: focused on actions on others student's objects.*

In this case, we obtained a total of 29 differential patterns Table 8-9 shows that in high achieving groups, students tended to interact more with objects created by other students, such as moving and adding links using other's concepts, either followed or preceded by periods of inactivity (keywords *NoOwn* and *Inact* in sequences I, J, and L). The keyword *NoOwn* appeared two times more often in the frequent sequences of the high groups than in the low achieving groups (in 42% and 22% of the sequences respectively). The presence of actions on student's own objects (*Own*) was similar in all groups.

*Alphabet 3: focused on Master map distance*

We obtained 28 *differential patterns* by analysing the encoded dataset. This includes contextual information of the concepts and links that belong to the crucial elements defined by the teacher. The patterns in Table 8-9 show that in high achieving groups, students tended to work with more crucial elements than low achieving groups. However, an analysis of all patterns that were found showed that there was not a large difference in the sequence of actions performed on the crucial elements (keyword *Cruc* was present in 87% and 84% of the patterns of high and low achieving groups respectively). The key difference was that high achieving groups interacted with less non-crucial concepts and links (keyword *NoCruc* was in 19% and 73% of the patterns of high and low groups).

Table 8-9 Top-4 most frequent sequences after applying differential sequence mining on each encoded dataset.

Alphabet 1	High achieving groups	Low achieving groups
A- {Menu-Mov-Same}>{Menu-Mov-Same}>{Menu-Mov-Parallel}		E- {Link-Add-Same}>{Link-Rem-Same}>{Con-Mov-Same}
B- {Con-Mov-Other}>{Link-Add-Same}>{Con-Mov-Same}>{Link-Add-Same}		F- {Link-Rem-Same}>{Con-Mov-Same}>{Link-Add-Same}
C- {Inact-Shrt}>{Con-Mov-Other}>{Link-Add-Same}		G- {Link-Add-Same}>{Link-Chg-Same}>{Inact-Long}
D- {Con-Mov-Other}>{Link-Add-Same}>{Con-Mov-Same}		H- {Inact-Long}>{Inact-Shrt}>{Con-Mov-Same}
Alphabet 2	High achieving groups	Low achieving groups
I- {Con-Mov-NoOwn}>{Con-Mov-NoOwn}>{Link-Add-Own}>{Inact-Shrt}		M- {Inact-Shrt}>{Con-Mov-NoOwn}>{Link-Add-Own}>{Link-Chg-Own}
J- {Inact-Shrt}>{Con-Mov-NoOwn}>{Con-Mov-NoOwn}>{Link-Add-Own}		N- {Link-Add-Own}>{Link-Chg-Own}>{Inact-Long}
K- {Link-Mov-NoOwn}>{Link-Mov-NoOwn}>{Con-Mov-NoOwn}		O- {Link-Chg-Own}>{Inact-Long}
L- {Inact-Shrt}>{Con-Mov-NoOwn}>{Con-Mov-NoOwn}		P- {Inact-Long}>{Inact-Shrt}>{Con-Mov-NoOwn}
Alphabet 3	High achieving groups	Low achieving groups
Q- {Con-Mov-Cruc}>{Link-Add-Cruc}>{Con-Mov-Cruc}>{Link-Add-Cruc}		U- {Link-Rem-NoCruc}>{Con-Mov-Cruc}>{Link-Add-Cruc}>{Link-Chg-NoCruc}
R- {Inact-Shrt}>{Con-Mov-Cruc}>{Con-Mov-Cruc}>{Link-Add-Cruc}		V- {Link-Chg-NoCruc}>{Link-Chg-NoCruc}>{Inact-Shrt}
S- {Link-Add-Cruc}>{Link-Mov-Cruc}>{Con-Mov-Cruc}		W- {Inact-Shrt}>{Link-Add-Cruc}>{Link-Chg-NoCruc}
T- {Link-Chg-Irr}>{Con-Mov-Cruc}>{Link-Add-Cruc}		X- {Con-Mov-Cruc}>{Link-Add-Cruc}>{Link-Chg-NoCruc}>{Inact-Long}

The sequences of the events extracted using this technique, provide some insights about the strategies followed by groups. We found that low achieving groups tend to have long periods of inactivity on the tabletop before or after creating links or performing a chain of actions that affect the layout of their concept map (e.g. action *Inact-Long* in patterns G, H, N, O and X). High achieving groups also had periods of inactivity, but these were shorter. Long periods of inactivity appeared two times more in the low achieving groups, followed or preceded by other actions (*Inact-Long* appeared in 48% and 22% of the sequences of high and low achieving groups respectively). There was no difference in the appearance of short periods of inactivity.

These findings suggest that, to discover the strategies followed by groups, this approach offers a limited view of the meaning of the actions. The frequent sequences that were found can be used to

build a model or benchmark to ‘detect’ if student’s actions are similar to either high or low achieving groups. However, the patterns themselves do not provide information about the process that groups followed during the activity that would be easily associated with group’s behaviours.

### 8.7.4. Process Mining Results

Figure 8-20 shows the resulting fuzzy models after applying the second approach to mine the process of both, high and low achieving groups where the conformance with their corresponding datasets was above 80%. Nodes of the graph represent categories of action blocks of activity and the edges the transitions between these. Each node contains: the name of the block category, the conformance of the block with the dataset, and the rates of active students who were involved in the activities ( $1u$ ,  $2u$  and  $+u$ ). Nodes with conformance rates below to 0.1 were not considered in the models. This include the majority of the block categories but disregards the actions that rarely appeared in the data and that would make the graph unnecessarily complex. The numbers next to the edge lines are indicators of conformance of the transitions with the datasets.

By visually comparing both graphs we can highlight that they share the same core blocks of activity. These include: the blocks *Inact-Short* and *Inact-Long* (marked with an orange small square in the top left of the node). We confirmed the results obtained with the sequence mining, where low achieving groups showed more long periods of inactivity compared with high groups (conformance of 0.68 and 0.95 respectively). Both models also have in common the categories *HighLow-NoOwner* and *HighLow-Owner* (blue markers) that represent activity that combined high and low impact actions on the group map (conformance of 1 and around 0.4 respectively). The last similarity in terms of nodes corresponds to blocks of low impact actions where students interacted with other student’s objects (*LowOnly-NoOwner*, red markers).

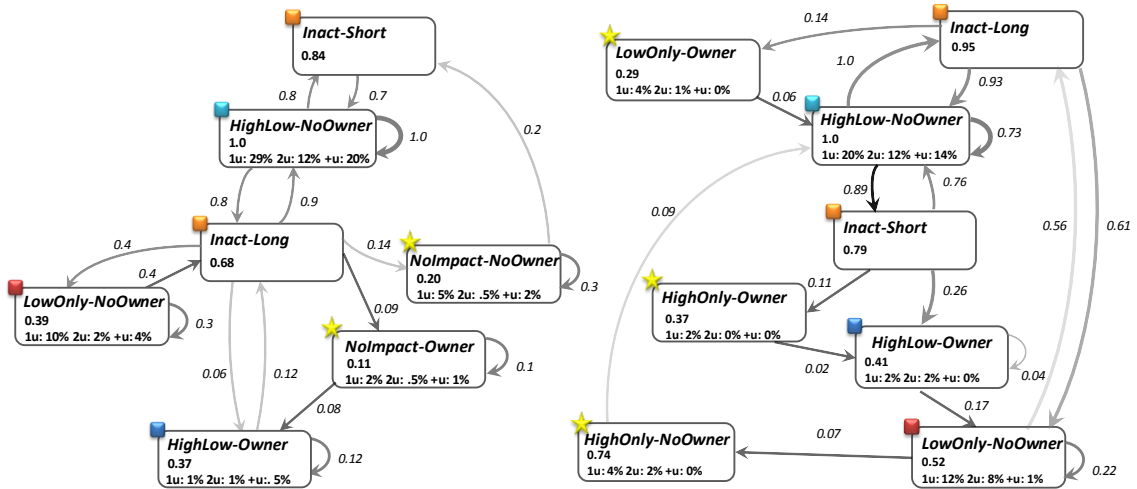


Figure 8-20 Fuzzy model generated from the activity of high achieving groups. Left: Fuzzy model of high achieving groups (Conformance: 86%, Cutoff: 0.1). Right: Fuzzy model of low achieving groups (Conformance: 81%, Cutoff: 0.1).

The nodes marked with a yellow star correspond to activity blocks that appear in one model but not in the other. High achieving groups, contrary to what was expected, had more blocks of actions with no impact on the concept map (*NoImpact-Owner/NoOwner*). However, both nodes had the least conformance with the model (0.11 and 0.2 respectively). In contrast, low achieving groups had blocks of activity with only high impact actions (*HighOnly-Owner/NoOwner*). The conformance of these blocks was not low (conformance of 0.37 and 0.74 respectively).

However, the main difference between the models is in the structure of the transitions. For the model of high achieving groups, there is only one transition between *different* blocks of activity that was, in addition, not very frequent (conformance of 0.08 between *NoImpact-Owner* and *HighLow-Owner*). The model of low achieving groups contains 5 transitions between activity nodes with a conformance of up to 0.17 (between *HighLow-Owner* and *LowOnly-NoOwner*). Additionally, we did



not find any observable difference in the actions performed on other students objects (*NoOwner*) and student's own objects (*Owner*). Next, we present the analysis of the number of students involved in the activities and the validation to determine if the observable differences can distinguish high from low achieving groups.

#### Active learners

Table 8-10 shows the results of the cumulative distribution of the number of learners involved in the periods of activity for both high and low achieving groups (partial rates displayed in the third line of text inside each node of Figure 8-20). Both high and low achieving groups had more than the half of the blocks of activity performed by a single student (54/55%). The main difference was that high achieving groups had blocks of activity in which more than two learners were involved, in comparison with low achieving groups (+u, 27% and 19% respectively). In low achieving groups, most of the blocks of activity were performed by either one or two learners.

Table 8-10 Distribution of the number of active learners in blocks of activity

Achievement	One learner (1u)	Two learners (2u)	More learners (+u)
High	55%	18%	27%
Low	54%	27%	19%

#### Validation

In order to validate that the two models generated by the fuzzy miner are different and can be used to distinguish the process followed by either high or low achieving groups, we estimated how accurately each model will conform to each group's activity. We performed a cross-validation to compare the level of fit of both models to the data blocks of each group by measuring whether the conformance of the model that corresponded to the level of achievement of the group was higher. Table 8-11 shows the confusion matrix for the results of this analysis. This indicates that the fuzzy model for low achievement could distinguish 100% of the low achieving cases; however, three high achieving groups had a superior conformance to this model. The conformance of the model of high achievement was higher for the high achieving groups in 17 of the 20 cases. The difference between the levels of fit of each model was statistical significant for high achieving groups (paired  $t(23) = 2.46$ ,  $p = 0.0219$ ) and very close to statistical significance for the model of low achievement (paired  $t(7) = 2.16$ ,  $p = 0.061$ ).

Table 8-11 Validation of the fuzzy models

		Predicted class	
		High	Low
Actual class	High	17	3
	Low	0	12

### 8.7.5. Section Summary

This section presented a novel approach to mine traces of collaboration of students working face-to-face on an activity linked with the regular curricula in the MTClassroom. Our goal was to exploit student's data that was unobtrusively captured in an authentic classroom in contrast to a controlled experimental setting. This can make our approach immediately applicable in a real classroom context equipped with the technology required. Sequential frequent mining was applied to find patterns of activity that differentiate groups. Results revealed interesting patterns that indicated students in high achieving groups worked more often in parallel, interacted with other student's objects and mostly focused on the crucial elements of the problem to solve. Regarding the configuration of the data mining method, especially for the Fuzzy process mining, changing some thresholds can produce different results. For example, the size of blocks of activity was set to the mean number of actions between two periods of inactivity (13 actions). We explored the generation of fuzzy models using two more heuristics for the maximum block size:  $\mu/2$  and  $\mu+\sigma$ . We obtained conformance rates as low as 60% for the block size heuristic of  $\mu/2$ , and very similar fuzzy models and conformance rates

for the heuristic  $\mu+\sigma$  compared to the one we used in the study. Even though these rates are lower than the ones we obtained using the  $\mu$  heuristic, a deeper analysis of the configuration of the approach is required.

The fuzzy miner tool was used to model the process that groups followed by grouping and categorising student's actions. This modelling proved effective in helping distinguish part of the process followed by groups. High achieving groups tended to build their concept map interweaving periods of focused activity with periods of tabletop inactivity. Low achieving groups, by contrast, had more transitions between different categories of blocks of activity including periods with only actions that caused high impact on the map. We also found that important strategies can be mined from early data. Our analysis was only performed on the data captured from the first activity of the classroom sessions. This gives time for the results of the analysis to be used by facilitators or group members in the classroom.

The knowledge generated by the sequence patterns and the fuzzy models can be used in several valuable ways. Firstly, derived group indicators can be displayed in a processed form on the teacher's dashboard to help them adapt in *real-time* their support to groups that most need attention. Secondly, the findings can be used to generate indicators of group learning to be shown to the teacher for after-class reflection or re-design of the activity or to reflect on student's performance or assessment. Thirdly, this information can be the basis to build student models that can be shown to learners to encourage reflection and self-assessment.

## 8.8. Chapter summary

In this chapter we report the key elements of an approach to help teachers enhance their awareness and control of classroom activities by making use of our enhanced tabletops, a teacher's dashboard and a linked wall display. To validate our approach the teacher designed small group collaborative activities linked with the curricula, based on the concept mapping learning technique, using our multi-tabletop classroom environment, the MTClassroom. This allows multiple small groups of students to work around a number of interactive tabletops, perform a series of tasks, discuss a topic and provide a solution to a case proposed by the teacher. The system automatically logs and processes contextual classroom information, identified student's actions on the shared device and all the steps that groups performed to build a collaborative artefact. Table 8-12 outlines the three types of data-driven teacher's support described in the chapter.

Table 8-12 Data-driven support provided to the teacher using the MTClassroom.

Section	Brief description	Main results
8.4	Supporting teacher's design and design assessment.	<ul style="list-style-type: none"> <li>• The delivery of indicators of the enactment can help the teacher perform post-hoc assessment of the design of the activities.</li> <li>• Indicators that were evaluated included: symmetry of participation and contribution, timing, artefact orientation and task progress.</li> <li>• The teacher is interested in obtaining automated information about the progress and quality of student's task.</li> <li>• The teacher requires controlling functions to control the script of the classroom activities.</li> </ul>
8.6	Supporting teacher's awareness and control.	<ul style="list-style-type: none"> <li>• Key controlling functions: blocking all tabletops, sharing particular tabletops in the wall display and broadcasting messages to all groups.</li> <li>• Indicators of group's performance can drive teacher's attention and intervention</li> <li>• Sequence mining can be used to discover differences between high and low achieving groups. E.g. in our study high achieving groups tended to work more frequently in parallel, interacting with elements added by other students and focusing on the crucial parts of the activity.</li> </ul>
8.7	Mining student's actions.	<ul style="list-style-type: none"> <li>• Fuzzy modelling can help discover the process followed by either high or low achieving groups. E.g. in our study we found that high achieving groups tend to have periods without interacting with the tabletop in between periods of activity.</li> </ul>

First, Section 8.4 evaluated our approach on three levels: assessment of how closely the class script was followed, measurement of equality of student's participation within each group, and evaluation of the achievement on the learning outcomes. This serves to provide teachers with tools to reflect on what happened in the enactment of the planned activities and to take informed decisions about how to re-design them for further improvement. Then, Section 8.6 presented the design and evaluation of the impact of providing minimalist orchestration tools for teachers to enable them to control and monitor their classroom activities. This study found that providing appropriate information to teachers can enhance their awareness and drive their decision making on what small group to attend next. Finally, Section 8.7 showed that data mining and process modelling techniques can be used to look for patterns that can help find differences between groups according to the teacher assessment. We proved that it is possible to mine face-to-face collaboration data unobtrusively captured in a classroom with the use of multi-touch tabletops.

Overall, MTClassroom offers functions to capture and centralise rich information about student's actions. This can be used in two ways. First, the *real-time* and carefully curated information is displayed to help the teacher run the class (deeply explored in the following sections). Secondly, the full data are made available for post-hoc analysis; this enables the teacher to assess the design and perhaps re-define it. We now summarise the outcomes our analysis.

*Interactive tabletops can give teachers new ways to address challenges in orchestrating an 'authentic' classroom.* We demonstrate that interactive tabletops, combined with other technologies, can give the teacher both enhanced control over, and improved awareness of, the multiple groups of students in a real classroom. Our work goes beyond previous research by providing mechanisms for the teacher to evaluate their classroom activity design, based on what actually happened in the enactments, as found in the data that can be captured by the interactive tabletops. Our design of the orchestration functions (e.g. freezing the tabletops, broadcasting messages to all tabletops, and flow control) primarily addressed needs that the teacher identified; we also took account of previous work (AlAgha et al., 2010; Mercier et al., 2012). This gave the opportunity to develop an environment for *classroom orchestration* and focus on the tools and data to help design, monitor and assess the authentic classroom activities.

*Interactive tabletops, and relatively simple technologies, can be used to capture sufficiently rich data to allow teachers monitor the effectiveness of such classroom orchestration.* This is aligned with our work, presented in the previous chapters, showing that even simple interaction data could be useful for teachers to evaluate group work and performance. Interactive tabletops can help teachers monitor the effectiveness of their design by reflecting on data about groups and class performance such as the rate at which propositions were created. In the classroom, there are many factors that can affect the enactment of the teacher's plans from one tutorial to the next. Our approach proved helpful in enhancing the teacher's awareness of the execution of each tutorial. For example, for the timing problems found, the teacher commented: "*These results are very good as a reminder that the structure for the next tutorials should be changed to give more time for activity 2 and final take away message. Ideally by making activity 1 shorter or making some variation in the activity itself*".

*Interactive tabletops can address real classroom orchestration problems that could not be addressed without this technology.* The classroom activity and the system's functionalities should be adapted or designed according to teacher's learning intentions. The orchestration commands should be provided to the teacher at their request. In our study, the options to freeze the tabletops and control the flow of the whole class were specifically requested by the teacher. Similarly, the teacher valued the understanding she gained about the class enactment, information that the teacher would not normally have. This is exemplified by one of teacher's comments on reviewing the results: "*I could probably know if the groups are working too slow[ly] but I wouldn't know straight away if they are introducing the 'important' concepts*" (from the teacher's master map) or if "*the contribution is lower for some students*".

*Our approach includes generic features (e.g. some orchestration and data capture functions can be used in other contexts), customisable features (e.g. the orchestration tool and some indicators), and features specific to the domain of the activity (e.g. concept mapping).* Choosing the right learning application depends heavily on the subject and particular learning goals. In our case, the teacher

considered that concept mapping was suitable for a case-study solving activity. Concept mapping has long been used in many learning contexts. This suggests that our system is likely to be useful for many other domains and contexts. The indicators of *collaboration and equality*; and *adherence to the class script*, can be generalised to other contexts. For other types of activities requiring different learning software, the indicators of *learning outcomes* would have to be identified accordingly.

We acknowledge some current limitations of our approach. The first is that the technology to capture student's actions is not yet developed to automatically record verbal interactions in the classroom. This is crucial in collaborative work, as was demonstrated in our studies where ideal conditions for face-to-face data capture (Chapter 7). However, our approach proved that even modest interaction data can provide insights for the teacher to enhance their *classroom orchestration*. The next chapter discusses in detail these limitations but also the great opportunities of our approach for further development and application.

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## Chapter 9: Conclusions and Future Work

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*"It is important to remember that educational software, like textbooks, is only one tool in the learning process. Neither can be a substitute for well-trained teachers, leadership, and parental involvement."*  
– Keith Krueger

### 9.1. Summary of Contributions

A number of interactive shared devices are slowly but surely making their way in various areas of application. For the case of learning and education, interactive tabletops hold the potential to contribute to the improvement of awareness and support for the times when students need guidance to collaborate face to face. We showed that the affordances offered by interactive tabletops can help the teacher orchestrate the classroom from different perspectives. These include: inspecting the enactment of the sessions, monitoring the process followed by each group, and enhancing their awareness of the quality of student's partial solutions, contributions and participation. Educational Data Mining and Analytics are also emerging fields that aim to exploit student's data to discover and make visible several aspects the learning processes. These can include student's strategies, patterns of collaborative behaviour, quantitative indicators of activity and quality of student's products. Our in-depth research on Computer-Supported Collaborative Learning and the principles of Orchestration offer a robust scaffolding to create data-driven solutions that can help teachers, students, researchers and designers enhance the various dimensions of small group collaboration and teamwork using shared devices.

Interactive tabletops can be used in a wide range of learning scenarios. For example, they can be used in connected small group activities in the classroom for a number of sessions. In this scenario, the teacher would be the main target user making use of the affordances of tabletops to help students reach their learning goals. They can be used in training settings where a single group of people engage in a collaborative activity. Another scenario would be the long-term group tasks performed by a team working on a project. In this case, learners would be interested in the affordances of tabletops to keep track of their milestones and products. In all such cases, the use of tabletops targets specific learning activities rather than general applications.

This thesis set out to explore learning contexts that make use of interactive tabletops. We investigated how interaction data can be automatically captured and exploited through data analytics techniques, in order to inform teachers and enhance their awareness of student's collaborative activity and the progress in their task. To achieve this, we proposed an approach grounded on the intersection of the three fields: Human-Computer Interaction (HCI), Computer-Supported Collaborative Learning (CSCL) and Educational Data Mining (EDM)/data analytics. We defined the problematic in terms of three main thesis questions:

1. *What information can be extracted from existing face-to-face interaction datasets?*
2. *What are the design features of a system that can unobtrusively capture and show interaction data?*
3. *How can interaction data be analysed and distilled to enhance teacher's awareness of group collaboration and the progress in their task?*

To address these questions, the thesis presented the TSCL-Conceptual Framework and the technological infrastructure which target the capture, analysis and presentation of key group's indicators of collaboration and learning. We operationalise both the conceptual framework and the technological tools, first, through a set of studies which aimed to make visible the nature of the collaborative data that can (and should) be captured from a face-to-face environment. We also explored ways in which these data can be exploited to analyse collaborative learning processes. Then, we showed the process to build and evaluate the technological infrastructure to gather student's interactions. We studied the impact of presenting distilled group information to the teacher. Finally, we demonstrated the implementation of the framework by deploying the technological infrastructure through two separate implementations: a small group working together on a learning task at a single tabletop; and an authentic multi-tabletop classroom. Figure 9-1 presents a summary of the thesis goals that address the questions described above. The figure also illustrates how each chapter of the thesis is associated with those. Chapter 4 explored the information that can be extracted from and the data analytics techniques that can be applied on existing face-to-face interaction datasets. Chapters 5 and 6 described key design elements for our system that can unobtrusively capture and show student's interaction data. Building on top of the previous chapters, Chapters 7 and 8 included the core studies of the thesis as they focused on analysing and distilling student's interaction data to enhance teacher's awareness of group collaboration and the progress in their task at a single tabletop setting and in the classroom

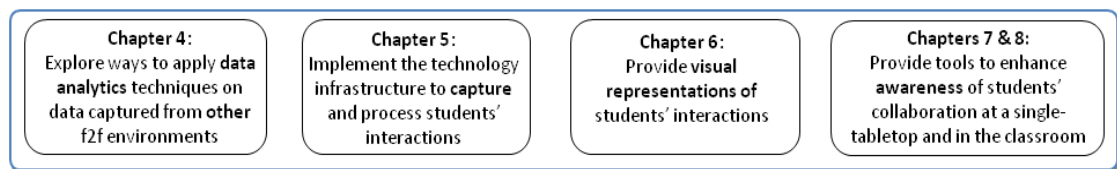


Figure 9-1 Summary of the thesis goals matching the thesis chapters 4-8.

We now describe how each chapter makes contributions to achieve the overall goal of the thesis.

### Chapter 3

**The main contribution of this chapter is the conceptual framework that can be used as a basis to build tabletop-based collaborative learning systems.** The chapter included the description of the learning situation that is addressed: a tabletop-based learning environment that can be implemented as a single tabletop, where learners come to build a joint solution, or as multiple tabletops in the classroom, where the teacher can design, plan, implement and assess authentic small group activities. We provided details of the components of the framework which includes the Theoretical Foundation (TF) and three operational modules: the Data Capture Foundation (DCF), the Data Analytics Foundation (DAF) and the Data Presentation Foundation (DPF).

Chapters 5 to 8 demonstrated, through the deployment of different implemented instances, that this framework makes it possible to provide teachers with valuable information, both under laboratory and in-the-wild conditions. This points to the promise for using our principles for applications other than concept mapping, the application that dominated our work. In this thesis, we used COLLAID to collect data, CMATE as the learning application and sequence mining approaches just to mention some examples. Following the same principles, other designers or researchers can use additional sensing systems such as speech recognisers or gaze trackers. By contrast, they may decide to not to sense speech (as we did in the studies in the classroom). Instead of concept mapping, they may create other learning applications. For example, our system COLLAID was used by other researchers (Clayphan et al., 2013d) to create Open Learner Models of groups of students using a brainstorming tabletop application called ScriptStorm (Clayphan et al., 2013a). The framework also opens up new avenues for further development and research, targeting other stakeholders (e.g. students and tutoring agents). Additionally, it suggests the need of integrating interactive tabletops with higher level learning management environments and other technologies.

#### Chapter 4

The contribution of this chapter is two-fold. First, **it presents three exploratory studies on collocated environments that are part of the first research efforts that applied data mining techniques** (classifiers, clustering and sequence mining) to discover patterns of interaction from face-to-face educational groupware. Each study provides particular insights that are described below. The second main contribution is **a set of considerations for designing a data-driven approach to support face-to-face collaboration**. Some of these considerations include the importance of differentiating student's input, the automated capture of student's speech, the need to build an unobtrusive solution to allow students to naturally collaborate and the need for capturing multiple dimensions of data. We built on those considerations to formulate and implement our own technological infrastructure and research approach.

The three exploratory studies are based on the analysis of data previously collected by other researchers in collaborative learning settings. The first, Study Waterloo 1, involved analysing student's data from a multi-display collaborative setting that they used to solve optimisation problems. The contribution of this study was an approach which automatically classifies the periods when a collocated group of learners is engaged in collaborative, non-collaborative or somewhat collaborative behaviour. The data mining technique only uses aggregated quantitative student's data. These data include verbal and physical activity of the learners with the system and other learners. The models presented in this study served as a foundation for designing the visualisation *Indicator of collaboration* that was presented in Section 6.4.3. This visualisation shows the "level of collaboration" detected by the system. In this study, the Best-First tree algorithm was used as it offered the second best accuracy and the coding of the resulting model was easier to implement as it could be simplified as a set of rules.

Study Waterloo 2 makes a contribution by demonstrating that the models found in study Waterloo 1 are also applicable to interactive tabletop settings. It also highlighted that, given the small size of the tabletop-based datasets available in the research community, it is necessary to collect larger datasets in order to generalise the findings. The explorative approach and the results of this study served as a foundation for addressing the first research question of one of the main studies of the thesis (presented in Chapter 7). The classification of each block of half a minute of activity was used to distinguish the groups that participated in that study according to their level of collaboration.

The contribution of the third study, Study Newcastle, was the analysis of tabletop data by taking into account the time and order of each action performed by students to shed light on the strategies followed by groups. The technique shown in this study also served for inspiring other researchers to follow up the idea of finding patterns that differentiate two datasets (now known as differential pattern mining). The study also served as a foundation for the sequence mining techniques applied to address four of the six research questions of the main studies of the thesis presented in Chapter 7.

Through the three studies, the chapter showed that it is possible to extract useful group indicators, through data mining and modelling techniques, as proposed in the Data Analytics Foundation of our conceptual framework introduced in Chapter 3.

#### Chapter 5

**The main contribution of this chapter is the basic technological infrastructure that can be used to capture and integrate multi-modal student's data.** The chapter presented a set of design principles to decide what data should be captured and how it should be exploited to build models or produce indicators of collaborative learning. These principles were presented in two lists: principles for capturing student's data (Data Sensing), and principles for formatting and mining tabletop data (Data Pre-processing).

The second element presented in this chapter is the main learning environment we used in our studies: CMATE. This system allows a group of students to decide on their strategies to build a collaborative concept map. The construction of CMATE is a contribution itself, since it was motivated



by the lack of available multi-touch concept mapping tools that can provide collaboration support, regardless of the hardware being used. It also offers a degree of flexibility to connect to other learning environments, load concept maps in other standard formats, and connect to other systems such as sensing and awareness enhancing tools.

Finally, the third element presented in Chapter 5 is COLLAID. This makes use of off-the-shelf hardware to add user differentiation and tracking features to currently available tabletop hardware. Key features of this system are: capture of user's speech, using a microphone array; unobtrusive touch identification, using an over-head depth sensor; and the integration of these data with the host tabletop system, using a standard network format and a database. We tested the effectiveness of the system in multiple tabletop technologies (including IR sensing layers, FTIR and SUR40 devices). The chapter shows how we operationalised the Data Capture Foundation of the conceptual framework introduced in Chapter 3.

#### *Chapter 6*

**The main contribution of this chapter is the process of designing and validating a set of group indicators, their visual representations, and a teacher's dashboard.** The first part of the contribution is the indicators that can be produced from traces of collaboration, proved effective in describing groups that show different behaviours. This was analysed by comparing the evidence of group behaviours that can be captured both automatically and from qualitative observations. The findings of this small study are important because they demonstrated that even though the quantitative student's information that can be automatically captured and analysed do not tell the whole story and details of groups' collaboration it certainly helps to obtain broad indications of some aspects of it. These findings provided scaffolding to and motivated the larger studies presented in Chapters 7 and 8.

The second elements, the visual representations of those indicators proved effective in fostering awareness and reflection when shown to teacher. In this chapter, the validation of these visual representations was mostly focused on offering teachers useful information of group work. This was the first exploratory work in the thesis investigating ways to show information to teachers and assessing the impact of such aiding tools for teaches to gain understanding of the group processes without actually inspecting the video recordings of the tabletop collaborative sessions. Further enhancements of some of the visualisations served as foundations for the design of prototypes of the teacher's dashboard and for the deployments in the classroom, as it was described in Chapter 8.

The third part of the contributions is a second set of visualisations that can be shown at a teacher's dashboard. The design of the dashboard was evaluated with real teachers to measures its effectiveness to 1) drive teacher's division of time for attending or intervening groups in a virtual multi-tabletop classroom; and 2) show detailed and distilled information about the progress of specific groups that can be revised after class. We presented two versions of the dashboard: a 'classroom' level and a 'group focused' versions. The former was a basis for the design and implementation of the MTDashboard (presented in Chapter 8).

The chapter makes a contribution by demonstrating how to implement aspects of the Data Presentation Foundation of our conceptual framework introduced in Chapter 3.

#### *Chapter 7*

**The main contribution of this chapter is the implementation of the conceptual framework and the technological infrastructure to study collaborative learning at a single tabletop in the lab.** The chapter presents a larger scale study, under controlled conditions, with detailed student's data capture. The study served to discover patterns of interaction that can help teachers, researchers or designers recognise aspects of the collaborative learning activity that can be used to distinguish high from low achieving groups of students. Additionally, it also served to analyse the evidence that can be obtained from the artefacts build by students to detect trends in student's collaboration, performance and transfer of their knowledge.

This chapter is one of the main outcomes of the thesis because it shows how the proposed theoretical framework can be implemented to provide deep information about collaborative strategies and patterns. The study described in the chapter shows how to implement aspects of the Data Capture and Data Analytics Foundation under controlled conditions, when ideal conditions are present. Those include the capture of differentiated verbal participation intertwined with the application logs and the progress of the task.

From the Analytics perspective we showed how sequence pattern mining, classification algorithms, clustering and simple analysis of artefacts (concept maps), can be automatically applied on a tabletop dataset to provide rich quantitative information. This chapter showed how the different findings and methods considered in the exploratory studies presented in Chapter 4; the technological infrastructure presented in Chapter 5; and the investigation of group indicators described in Chapter 6 were foundations for analysing the traces of student's individual and collaborative learning at the tabletop.

### *Chapter 8*

**The main contribution of this chapter is the operationalisation and integration of all the components of our conceptual framework and the enhancement of our technical infrastructure in-the-wild, through our multi-tabletop classroom.** The chapter presents MTClassroom, which was designed to capture interactions of students working in small groups, and provide the teacher with the infrastructure to design, control, monitor and assess collaborative activities. This design was built from a foundation that was teacher-driven. It drew upon principles of collaborative learning and orchestration, with a particular emphasis on empowering teacher's classroom control and awareness.

Two sets of authentic tutorial sessions were taught in two different school periods for two different university-level subjects. There were 376 students involved in these tutorials. The system provides full interconnection between enhanced interactive tabletops (COLLAID), a data repository and a teacher's dashboard (MTDashboard). This latter allows the teacher to perform key functions to control the collaborative script and have access to simple visualisations of group's collaboration in *real-time*. These visualisations can help teachers decide which group may need their attention. The system can also support deeper analysis of student's data to discover patterns of student's interaction automatically, using artificial intelligence techniques. These are for use after the class. The importance of this chapter was also in showing that the aim of the thesis and the proposed approach can be delivered into real classrooms. It additionally introduced the use of the notion of Orchestration to integrate the different topics addressed in the thesis. This includes the use of data mining in the classroom, the visualisation of group indicators on a teacher's dashboard, the use of other indicators of the class enactment to inform teachers and the benefits of automatically and pervasively capturing individual and collaborative student's data.

### *Closing remarks*

The series of carefully designed user studies presented in the thesis explored several important aspects of collaborative learning aided through interactive tabletops and the analysis of student's data, using visualisations and data mining techniques. This analysis proved that it is possible to make visible key aspects of group's collaboration for teachers and researcher. The elements of our approach have been carefully designed to address our research questions. These were focused on three ordered steps: the exploration of the feasibility of the approach, the construction of a novel solution and the execution of the conceptual proposal, both in the lab and in the classroom. Each element of the studies described served an important role in showing the value of a data-driven approach to support awareness of student's collaborative interactions.

The thesis statement —**design, implement and evaluate the conceptual and technological infrastructure that capture student's activity at an interactive tabletop and analyse these data through Interaction Data Analytics techniques to provide support to teachers by enhancing their awareness of student's collaboration** — is supported by the formulation of our conceptual framework and the various instantiations of the approach in multiple dimensions:

1. small and large scale studies;
2. implementations in the lab and in-the-wild;
3. validations with teachers, users, students and through data analysis;
4. multiple data analysis techniques: empirical observations, visualizations, statistics, data mining, process mining;
5. and various technological deliverables such as our tabletop concept mapping tool (CMATE), our system to capture multi-modal group's information (COLLAID), different versions of teacher's dashboards and our multi-tabletop classroom (MTClassroom).

Our work has pioneered a number of new areas including the application of data mining techniques to study collaboration at the tabletop (Martinez-Maldonado et al., 2013c), a plug-in solution to add user-identification to a regular tabletop using a Kinect sensor (Martinez-Maldonado et al., 2011b), and the first multi-tabletop classroom used to run authentic collaborative activities associated with the curricula (Martinez-Maldonado et al., 2012d).

While the mechanisms, interfaces and studies presented in this thesis were mostly explored in the context of interactive tabletops, the findings are likely to be relevant to other forms of groupware and learning scenarios that can be implemented in real classrooms. Through the mechanisms, the studies conducted and our conceptual framework, this thesis provides an important research foundation for the ways in which interactive tabletops, data mining and visualisations techniques can be used to provide support to improve awareness of small group processes. Our approach provides a teacher with a whole new dimension of awareness of several groups in their classroom, in terms of collaboration and the on-going progress of the learning activity. This has not previously been possible for small group face-to-face collaboration that is so important in classrooms.

## 9.2. Future Directions

Nowadays, learners can interact with other learners, teachers and sources of information through a great variety of both pre-existent and emerging mediums. This is afforded by the proliferation of internet connectivity, intelligent tutoring systems, a wide range of personal learning environment (PLE's), Learning Management Systems (LM'Ss and VLE's), pervasive systems and personal devices. However, educational technology in general, including the use of multi-touch interactive tabletops, does not necessarily produce a drastic impact on education. In words of Larry Cuban (2012): "...by 2023, uses of technologies will change some aspects of teaching and learning but schools and classrooms will be clearly recognizable to student's parents and grandparents". The different facets of the research work presented in this thesis open up a number of opportunities for further development specifically targeting the enhancement of instruction and learning support.

In this thesis we focused on showing that our TSCL-Conceptual Framework can be effectively applied to help teachers, researchers and designers gain awareness and understanding of a number of aspects of small group collaboration. However, the application of the TSCL-CF can be extended to a wide range of areas of research and practice. The description of our future work is aligned with current educational technology trends and can be condensed into three main objectives: to enhance the educator effectiveness, provide personalised/adapted learning experiences and contribute to the development of collaborative learning skills. Next, we present the five main specific areas of future work of this thesis.

*Making visible aspects of student's collaborative work that otherwise would remain invisible.*

The work presented in the thesis regarding the student's data exploration, analysis and distillation belong to an emerging area of research which integrates applications of educational data mining / analytics and computer-supported collaborative learning. The analysis of student's collaboration data using data mining techniques can help teachers understand differences in behaviour for early detection of possible problems in group work. Our analysis provided partially supervised solutions to detect levels of collaboration (Chapter 4), to discover frequent sequential

patterns from students interactions (Chapters 4, 7 and 8) and to group similar patterns to facilitate their association with collaborative strategies (Chapters 4 and 7). Further work must be done to incorporate the rich information that can be provided by the domain itself to consider the quality of the work, learning gains or individual student's performance.

Another key area for further development is the use of analytics tools to inform teachers of aspects of collaborative work, or the processes followed by group members, that would otherwise remain invisible. We showed that our process mining application or even simple visualisations of student's data can enhance teacher's awareness in the classroom or drive reflection (Chapter 8). These studies can motivate future research questions inspired by teacher's needs for orchestration of connected collaborative activities. Patterns of interaction associated with either high or low achieving groups, discovered offline, can be used as a base for comparison in *real-time*, so that the systems can generate automatic *real-time* alerts that can help teachers drive their attention to groups that potentially need closer coaching. Further solutions may include the application of data mining techniques running in *real-time*, so that they can incorporate new data to improve the type of alerts provided to the teacher.

#### *Helping teachers orchestrate a multi-technology classroom ecology.*

The work presented in this thesis, that addressed *classroom orchestration* issues, focused on the use of multi-touch tabletop technologies and sensing systems. We also explored the ways other technologies, namely a public whiteboard, a teacher's dashboard, a central data repository and sensing systems, can be integrated as key interconnected elements of this classroom. However, future work should consider the inclusion of other learning devices or sources of student's data as a part of the classroom ecology. In our studies in the classroom, even when personal devices, such as smart phones and tablets, were freely used by students, mainly for reading, they did not belong to our interconnected ecology. Further research and development effort needs to be done on enhancing the interconnection of multiple learning technologies (including personal devices, pervasive furniture, shared devices and other non-digital tools) and unobtrusive sensing technologies (tools to capture aspects of the process and "who does what") while keeping the classroom environment as authentic as possible.

#### *Connecting learning activities across classroom sessions and learning environments.*

There are countless possibilities for exploring the space for orchestrating connected learning activities across classroom sessions using several *orchestrable* technologies, like in our multi-interactive tabletops. Thus, future work can explore the role of the teacher in designing connected activities performed before or after the classroom sessions. This includes the use of shared devices, such as tabletops in the classroom, and other types of systems that can be accessed online, to maintain the support of collaborative activities across learning environments and devices. Future work can also explore the affordances of the interconnection of activities to support the movement of artefacts from one environment to another. In this way, students may build artefacts in the classroom that can be edited after class using a web based system, or by contrast, working in the classroom with objects created in previous learning sessions, using other systems (similarly to studies in Chapter 7). A promising option would be to interconnect the products and student's data generated in the classroom sessions with VLE's, or similar larger systems. This can help teachers and students to work on a central learning management system for activities conducted in the classroom or outside the classroom. This integration is important if we consider that interactive tabletops may be used in only some classroom sessions, while other activities occur through online systems or outside the scope of any technology.

#### *Exploring other learning situations and tabletop tools.*

In this thesis we explored some different learning activities (in Chapter 4, Digital Mysteries and an optimisation task) but the core of the studies were conducted using a collaborative concept mapping application. Moreover, the learning situation that was targeted in this thesis assumes that all students had the same opportunities of participation and they are intended to contribute equally. The activities we explored were symmetric in the sense that all students shared the same learning

objectives, could perform the same range of actions and did not have differentiated roles. Further research can explore the implementation of our approach to capture and analyse student's data enacting other learning activities and using different tabletop applications. More specifically, a deeper exploration is needed in non-symmetric team work tasks that may require students to assume different roles, have access to different pieces of information (as in jigsaw activities) or contribute with different types of expertise.

*Producing a collaboration-aware interactive tabletop system.*

In Chapter 4 we presented our sensing system that can capture multi-modal student's data while they work at an interactive tabletop. While our novel system can enhance currently available tabletop hardware, there are various alternative sources of student's data that can be further integrated and pervasively captured. Some student's data that may be useful for designers or teachers may include student's gaze, gestures, and dimensions of student's speech such as pitch, volume, enthusiasm, level of interest or persuasiveness. Another possibility for further research includes improving the data capture in-the-wild for example, teacher's actions, the verbal participation of each student, or at least each group.

*Analysing the content of speech and other dimensions of student's collaboration at the tabletop.*

Even though the capture of student's data at interactive tabletops can be enhanced by emerging sensing technologies, additional research is needed to find the ways in which multiple sources of data can be integrated and analysed. One area for further development is the reduction of the dimensionality of the data to extract the information that is relevant in order to address specific research or teacher's questions. Additionally, richer student's data, such as information about location, student's movements or the content of speech, may provide very important information about the quality of student's collaboration at the tabletop. In this thesis, our analysis focused on quantitative aspects of speech that only provided information about conversation frequency, length and turn taking. Future work should consider the content of what student's say if this information can be automatically captured through automated transcription.

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## A.2. COLLAID Infrastructure and Evaluation

This Appendix section provides details about the implementation and an evaluation of accuracy of COLLAID according to a number of conditions of scalability (number of users), activity density and multi-touch gestures. The evaluation exercise was conducted in collaboration with Christopher Ackad and Andrew Clayphan. Parts of this Appendix section were published in (Clayphan et al., 2013b).

The primary purpose of COLLAID is to provide a simple to use touch identification solution, that can be used in-conjunction with any currently available tabletop system. Its design is based on the following set of implementation goals:

1. Real-time – The system should work almost instantaneously and provide feedback to users being identified.
2. Scalable – The system should handle increasing levels of activity and still be able to identify touches.
3. Support for multiple users – The system should support a minimum of four people working collaboratively.
4. Seamless – The system should work with current tabletop technology without requiring the user to wear physical devices or need to engage with special icons or tokens on the display. Technology from the viewpoint from the user should be imperceptible. It should also be able to work with different operating systems.
5. Low Cost – Be inexpensive, such that designers can take advantage of the system we offer, deploying it quickly to an installation to see if the system yields benefit for them.

### A.2.1. Infrastructure

COLLAID uses an off the shelf Kinect sensor, mounted above the tabletop. The software was designed to integrate with any tabletop device. It is built using the OpenNI<sup>1</sup> Kinect drivers and SDK allowing for cross platform support. It has been tested on a PQLabs touch overlay running Ubuntu/Windows, and a Samsung SUR40 (Microsoft Surface 2) running Windows. Our system works by taking a depth image, which after the background has been eliminated, can detect any object, person or body above the surface, as shown in Figure A-2.

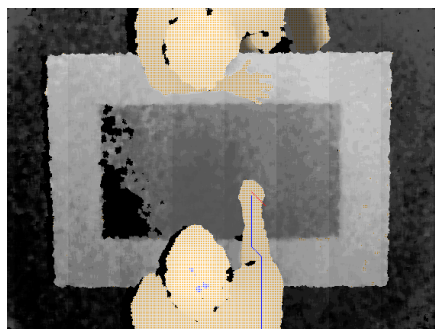


Figure A-2 Depth Image from the sensor.

COLLAID is first calibrated to record a baseline of the interactive tabletop and its surroundings without users around it. This only has to be completed once when the Kinect is first mounted. The application can easily be configured for use up to 6 users, support different heights of the depth sensors and even cope with changes in the inclination of the interactive tabletop. The touch

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<sup>1</sup> <http://www.openni.org/>



identification software and the tabletop application are linked through a simple handshaking network protocol. Each time the application receives a touch event from the hardware it sends the touch identification number and the coordinates to the touch identification system. This resolves the user who performed the touch through an algorithm that goes through the captured depth images from the sensor. The result of this algorithm is sent back to the application. This includes the touch identification number and the position of the user associated with that touch.

Different algorithms can be used to perform the touch identification using the depth information. For the studies in this thesis, a weighted greedy best-first-like algorithm was used. The purpose of the algorithm is to trace a line between the touch and the body or head of the user being identified. The algorithm is run each time a user makes contact with the interactive surface as following (refer to Figure 5-8 in Chapter 5):

1. A user touches the surface so the regular tabletop application receives the coordinates of the touch and sends the coordinates to COLLAID.
2. COLLAID matches these coordinates with the depth image. Following, the algorithm the most proximal hand around a touch to be followed (scan radius =  $r$  pixels).
3. A simple implementation of a greedy search algorithm chooses the direction of the path that has the maximum body parts detected. The algorithm considers 8 possible radial equidistant directions around the touch and each stepping node.
4. Steps (2) and (3) are repeated continuously until a minimum distance to a user's head has been reached or an upper bound of repetitions are achieved. Weights are applied to each of the 8 directions so the algorithm does not go back on itself, motivating the search to continue towards a user, instead of going back to the user's finger.

COLLAID employs a modular approach. Figure A-3 shows the composition of our plug in system, in-conjunction with a tabletop application, a tabletop display, and a depth sensor. Items represented by dashed boxes, indicate modules that can be easily interchanged. Additionally, our touch identification system can be flexibly integrated with a number of other modules, such as a head tracker (a) or user authentication system (b), (shown in the orange boxes), which can enhance the current capabilities of the system, as well as provide new functionality. Indeed, an implementation of a user authentication system connected to COLLAID is presented in Appendix A.3

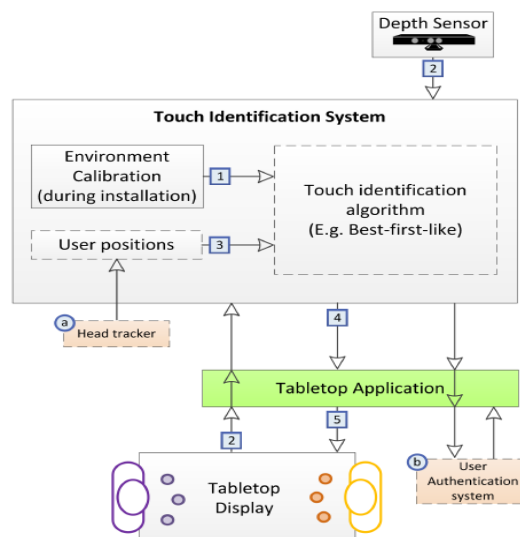


Figure A-3 Modular structure of COLLAID; and how it fits within a tabletop application, and the potential for other components to plug into it.

The following occurs when the system is used with a tabletop application. The steps refer to those in Figure 3. They are:

1. The touch identification system is calibrated, only once, during install of the sensor device.
2. The depth sensor sends information to the touch identification system. Also, the tabletop display sends information to the tabletop application which in turn transmits this information, formatted with a touch identifier (via TCP) to the touch identification system.
3. The user locations are read into the system, allowing the touch identification algorithm, to make a touch location to a user. While this particular system assumed fixed positions, the system can be enhanced to track movements of the users, for example with a head tracker (a), in that case, the information from that system would be in place of the current fixed user locations.
4. Results with user id and touch identifier, are sent back to the tabletop application.
5. The tabletop application provides feedback to users at the tabletop, such as a uniquely coloured halo corresponding to the user, or an adapted widget.

## A.2.2. Evaluation

In order to test the effectiveness of COLLAID to differentiate users, an evaluation suite was implemented, with an analysis tool to interpret collected results. This allows us to evaluate our touch identification mechanism across a range of different dimensions and provide the foundations towards the systematic assessment of touch identification accuracy for other vision-based systems.

A number of different conditions that are important for designers were identified. This includes the sort of questions for which designers would like to have answers to. We now explain the importance of each:

*Number of users:* The number of users supported by an identification system is important as a key role for tabletops is to support small group collaboration. Application designers should know the effect of group size on accuracy. This aspect interacts with all the others so it is important to test those conditions for different numbers of users.

*Touches close to the user:* This means directly in front, within a hands-length from the edge of the tabletop (see Figure A-4, 1). This is important for cases where personal controls are located near a user. It is also the area for most natural interaction by a user, indicated by work on territoriality. Additionally, this region may be prone to occlusion from a user's body or head, obstructing line of sight to a sensor (an inherent problem with identification systems that are above the tabletop).

*Touches near other users:* This is where two or more users' touches are in close proximity to one another (see Figure A-4, 2). This may be important for activities where users work together on the same interface element, for example collaborative gestures.

*Arms/hands Crossing:* Inevitably there may be situations, where hands or arms are likely to cross (see Figure A-4, 3). For in-the-wild deployments, this may happen even if not part of the planned design. This case is important as it is likely to be an inherent cause of errors for several mechanisms that rely on simple analysis of hand or arm positions.

*Multi-finger:* For systems that support multi-touch gestures, a designer may wish to know how these affect accuracy (see Figure A-4, 4). For example, touches associated with scaling or rotating a widget, are commonly done with 3 fingers – and these fingers are close to one another. This may cause errors due to occlusion.

*Random (Activity Density):* This is a proxy for authentic activity levels at a tabletop. It is valuable to assess the accuracy for touch points that are distributed randomly across the full surface of the tabletop. We propose a variable number of touch points since a designer may create an application where people need to touch multiple points, with users deciding the order in which to do that.

*Standing/Seated:* Designers may have their users standing or seated around a tabletop. When users stand, errors may be caused if their head or body obscures line of sight for above the tabletop methods.

*Overall:* This is total accuracy over tests that cover all the above cases. This is a useful starting point for comparing systems, although cases listed above are more valuable if the designer has a set of intended interaction designs in mind.

*Individual Variability:* This is whether accuracy values vary across users. For example, many errors may come from one participant in testing. It may also be due to classes of errors that are more likely to occur if a user is at a certain location around a tabletop.

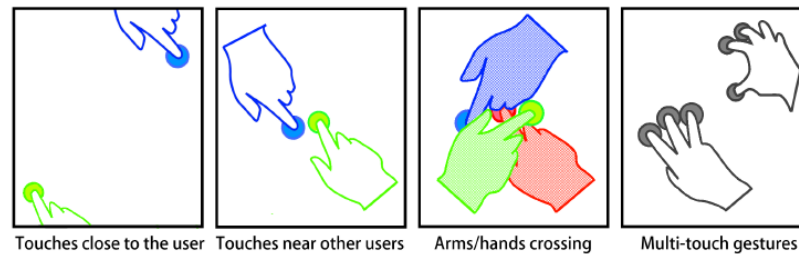


Figure A-4 Examples of test touch conditions that were evaluated.

An evaluation trial was divided into two phases: participants seated, and then standing. This helps validating the feasibility of this vision system associated with the possible impact of occlusion related to posture. For each phase, two test cases for: touches close to the user, touches near other users, arms/hands crossing and multi-finger conditions are performed; and ten for the random condition (activity density), corresponding to 1 to 10 touch points per user (see Figure A-6). Each test is repeated twice. Per evaluation trial, this is 90 unique tests. This results in 360 when accounting for physical condition and repetition. Each complete trial is tested with different number of users at the tabletop (see Figure A-5). Including setup time, an evaluation trial of 360 tests, takes less than 75 minutes.

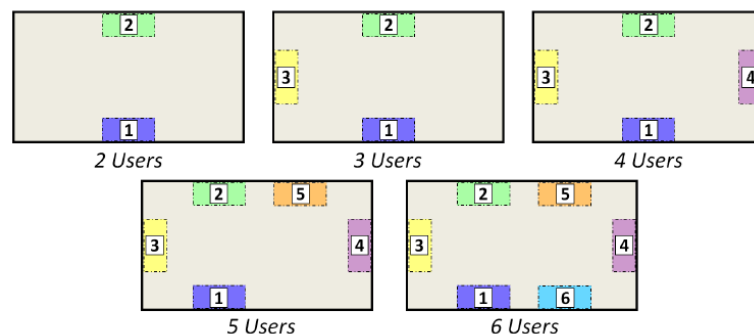


Figure A-5 Placement of users around the tabletop.

While the configuration of the tests served to evaluate aspects of our touch identification system that are of interest, the system can accommodate other designer needs, either choosing from a set of provided test cases, or by using our test configuration tool (Figure 6) to generate further test cases. For each test case, there is a 3 second preview window before participants can touch their designated touch points. The tabletop in the preview window takes on a light grey background (Figure A-6a). This gives participants time to see what they need to touch. After the preview window, the system becomes active. This is indicated by the background changing to black (Figure A-6b). The touches from users are recorded to the database only when a test is active.

When a point on the tabletop is touched, the colour of the point changes from its original colour (Figure 9a) to a default colour of grey (Figure A-6b) to signify the point as being touched. When all touches are completed in the current test, the system advances to the next test. When all tests are complete, the system prompts participants to move their seats, and stand, or if at the end of the standing phase, asks the number of users in a group to change, before starting a new series of tests. In summary, a group of users sit (or stand) in front of their colour-marked by a rectangle on the tabletop. COLLAID gives a prompt that tests are about to start. There is a preview window before the system records users input. After all points in a test case are touched, the next test case begins.

Additionally to the extensive testing of our touch identification system in the PQLabs touch display, the system has successfully been tested in a custom made FTIR-based tabletop and a Samsung SUR40.

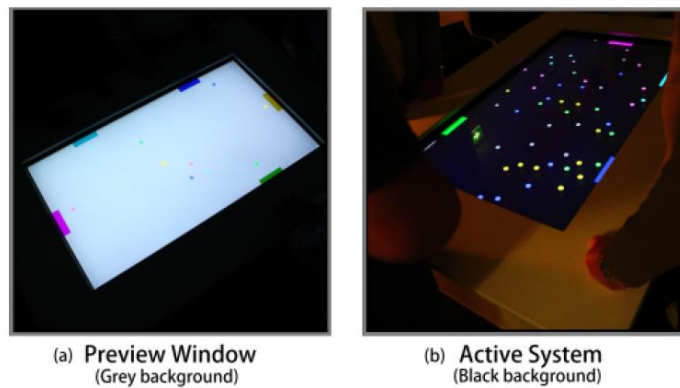


Figure A-6 Left: Preview window and Right: Random (Activity Density) condition.

### A.2.3. Results

COLLAID was evaluated with a group size of 2, 3, 4, 5, and 6. There were 2 evaluation trials, for a total of 12 different users (mean age 25, median age 26, 83% male, 17% female). As per the specifications for each trials, users completed the conditions of standing and seating, repeated twice. In total, 720 test cases were performed, with 10702 touches evaluated.

Results are across the different conditions: touches close to the use; touches near other users; arms/hands crossing; multi-touch gestures (Table A-1); random touch points (activity density) (Table A-2 – for brevity, a subset of results are shown); users standing/seated (Table A-3); and overall results – per group of users (Table A-4).

Table A-1 Results of conditions: Results of condition: touches close to the user, touches close to other users, arms/hands crossing and Multi-finger gestures.

Users	Accuracy			
	Touches close to the user	Touches close to other users	Arms/hands crossing	Multi-finger gestures
2	100%	97%	75%	100%
3	100%	81%	92%	100%
4	100%	94%	81%	100%
5	98%	84%	88%	99%
6	98%	83%	83%	97%

Our system performed well for touches close to the user, 100% for 2-4 users and 98% for 5-6 users (see Table A-1, column 3). It shows COLLAID is well suited when touches are required to be in close proximity to a user, such as in a personal control panel. For touches near other users, accuracy declined in relation to the number of users present. For 2 users – 97%, down to 83% for six users (see Table A-1, column 4). This could be an issue for some systems, but knowing this, may allow tabletop application developers to design applications, that reduce the promotion of gestures or touches near other users, for example, co-locating users at opposite ends of a table. For arms/hands crossing, the results were across the board, with an average of 84% and even dropping to 75% for 2 users (see Table A-1, column 4). This was partially expected, given the nature of our algorithm – however it is noted that these test cases forced users to occlude each other. For multi-touch gestures, looking at the issue of possible occlusion due to multiple touches in close proximity to one another, and performed by the same hand – results were 100% for 2-4 users and 97% or higher for 5-6 users (see Table A-1, column 5).

For the random touch position (activity density) test cases, result accuracy decreased in relation to the number of users, with a result of 92% or higher for 2-4 users, and 77% or higher for 5-6 users (see Table A-2). Even in adverse unplanned conditions, the system still reported a high accuracy.

Table A-2 Results of condition: Random touch points on the tabletop.

Users	Touches per user	Total touches	Wrong touches	Accuracy
2	1	16	1	94%
	5	80	2	98%
	10	160	4	98%
3	1	24	2	92%
	5	120	10	92%
	10	240	16	93%
4	1	32	2	94%
	5	160	15	91%
	10	320	34	89%
5	1	40	0	100%
	5	200	25	88%
	10	400	500	88%
6	1	48	11	77%
	5	240	35	85%
	10	480	83	83%

When posture is taken into account, there was a marginal accuracy increase of 3% for the seated condition over the standing condition for 4 or more users (see Table A-3). This is somewhat expected, because when an individual stands, they can reach any part of the tabletop, by extending their arm, or more likely, leaning with their body, a side effect – obstructing the line of sight to the depth sensor above the tabletop.

Table A-3 Results of condition: users standing and seated.

Users	2	3	4	5	6
Standing	96%	94%	90%	87%	84%
Seated	98%	94%	93%	90%	87%

Overall, the accuracy of the system is mostly affected by the proximity of student's hands and bodies. Even though the vision-based system showed such limitations these are not significant if taken into account in the design. The overall accuracy is above 90% for settings with 2-5 users. The system accuracy is lower when the number of users around the tabletop increases (see Table A-4). Moreover, the situations where two users have to cross their hands to reach opposite sections of the table were the most significant sources of touches wrongly differentiated.

Table A-4 Results: overall accuracy per number of users.

Users	Total touches	Wrong touches	Accuracy
2	1168	57	95%
3	1752	111	94%
4	2336	183	92%
5	2911	287	90%
6	3496	468	87%

### A.3. Exploring User Identification with COLLAID

This Appendix section provides details about a prototype that affords user identification using COLLAID and a personal mobile application. This explorative prototype was conducted in collaboration with Christopher Ackad and Andrew Clayphan. Parts of this Appendix section were published in Work-In-Process of CHI-12 (Ackad et al., 2012).

Identifying user actions on the tabletop is important to allow users to share and keep track of their personal information, to associate individual contributions in collaborative activities and to provide personalised experiences. To date, there is no nonobtrusive way to accomplish user identification and tracking at the tabletop. In the Thesis Section 2.3.2 we reviewed a number of previous systems, such as DiamondTouch (Dietz and Leigh, 2001), and even COLLAID, that can track users but not identify them. HandsDown (Schmidt et al., 2010a), which used hand biometrics, authenticated users but did

not support walk up use. Previous systems for user identification have required users to manually associate their identity with specific gestures (Schmidt et al., 2010a) or gadgets that they have to wear (Dietz and Leigh, 2001) which made them less seamless.

We explored the use of personal devices to provide a method for continuous user identification on tabletop surfaces. In this system, all users are tracked using COLLAID. When a personal device is put down by a user, the tabletop locates it on the table, connects to the device, and associates the identity from the device to the tracked touches on the tabletop. The personal device can support content sharing on the tabletop and controls for privacy. In our system, once identified, tracked users are only removed from the system tracking after they are out of range of the overhead camera. This permits flexibility for users to move, change the position of their devices, pick it up and even place it in their pockets. It also allows monitoring physical interactions around the tabletop even if users change seats or move around. The contribution is to provide a prototype that combines both user tracking and identification on the tabletop that is seamless and unobtrusive to the user.

### A.3.1. Prototype Motivation

Since so many people have personal mobile phones that they usually carry, it is natural to explore ways to make use of a mobile phone in conjunction with embedded tabletops. Previous work has explored mechanisms to track and connect multiple mobile phones with interactive surfaces with the purpose of sharing personal content. Our vision goes beyond previous work, as we aim to provide user identification and subsequent tracking of that user's actions at the table. Importantly, it operates in conjunction with a wide range of tabletop hardware and standard mobile phones (Afforded by COLLAID and personal mobile devices, see Figure A-7). Its combination of identification and tracking can support: personalisation; context aware applications; and new services for users and researchers.

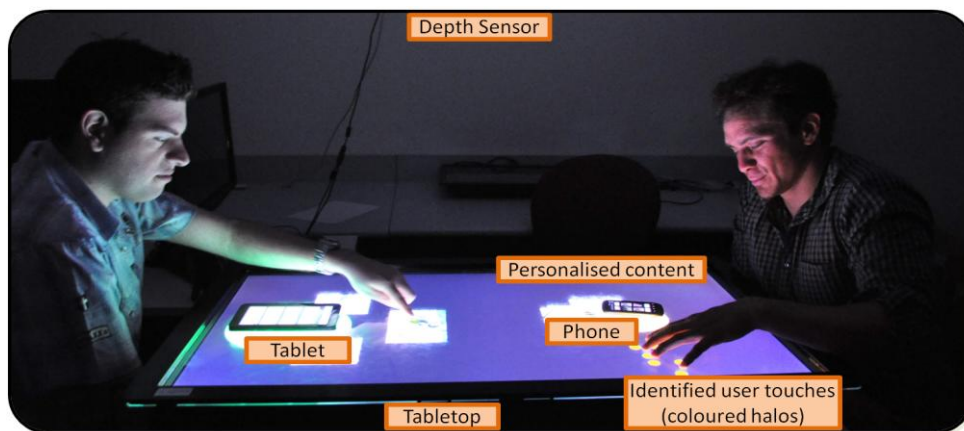


Figure A-7 The User Identification System: a high level overview.

In this scenario there are two users. Both have been identified by the system – indicated by green halos on the left user's touches and yellow halos for the user on the right.

The system consists of:

1. A depth sensor mounted above the tabletop.
2. A tabletop. We use an off the shelf multi-touch screen.
3. Personal devices. For example a tablet or phone.

The system allows:

1. Identified user touches.
2. Personalised content to be sent from the device to the tabletop.

### A.3.2. Infrastructure

The system integrates an interactive tabletop and personal devices, using a depth sensor for continuous tracking of touches that are linked to an identified user. Figure A-7 shows the system in use. We now discuss its architecture. The system operates in the following steps (see Figure A-8):

1. Depth Sensor sends data about people and objects to COLLAID.
2. The System Application forwards received data from the tabletop to COLLAID.
3. COLLAID determines the users and objects and starts to track them anonymously.
4. The System application upon receiving object data (from Step 1) sets a colour under the object to initiate a handshaking protocol for establishing an identity.
5. The phone detects the colour with its camera and sends it to the system application for it to be processed.
6. The system application matches the processed data from COLLAID to the data from the tabletop and displays feedback on the tabletop.

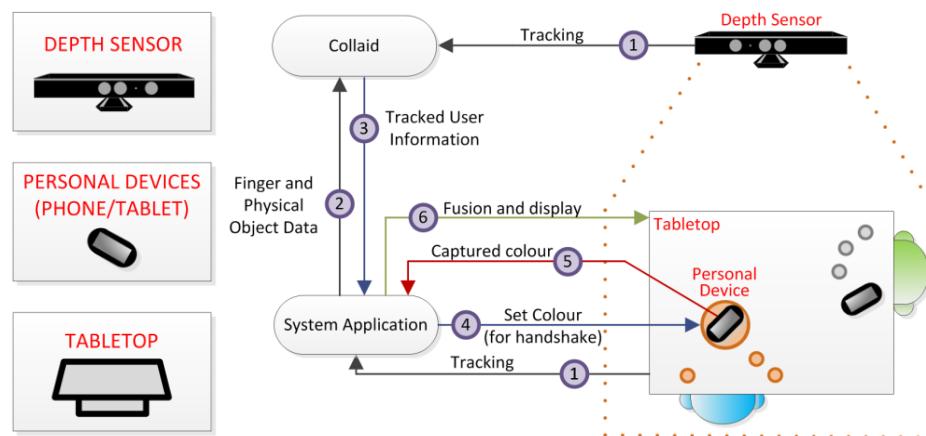


Figure A-8 The User Identification System: infrastructure.

This architecture makes it possible to identify and track users on general tabletop hardware, unlike the special hardware for user tracking of DiamondTouch (Dietz and Leigh, 2001). The features of our prototype are summarised in Figure A-9.

Feature	Explanation
Multi-touch	Can be integrated with arbitrary multi-touch hardware.
Multi-user	Can deal with many users, limited by tabletop size.
Tracking	Follows user movement and touch interactions on the tabletop.
Identification	Links touches and user objects to an identified user.
Personal devices	Devices allow for user identification and permit sharing of digital resources.
Inexpensive	The system uses off the shelf items, thereby allowing other systems to easily integrate.

Figure A-9 The User Identification System: features.

Continuous user tracking is performed by COLLAID. The COLLAID system can plug into various available tabletop hardware to capture information around the touches and objects on the

interactive surface. It makes use of an overhead depth sensor<sup>1</sup> that captures each user's body and arm positions of a number of users above the interactive surface. We pair the depth images generated by the depth sensor with each touch performed on the interactive tabletop identifying the finger that is touching the table in that position, at that precise moment. A personal device, such as a mobile phone or tablet (with equipped camera), supports the mechanism for linking a person's identity to a tabletop. It provides the means to associate an identity with a tracked user (see Figure A-10). We used a HTC Nexus One and a Samsung Galaxy Tab both running Android 2.3. We implemented a simple handshaking protocol on the device to link its identity with tracked users on the tabletop.

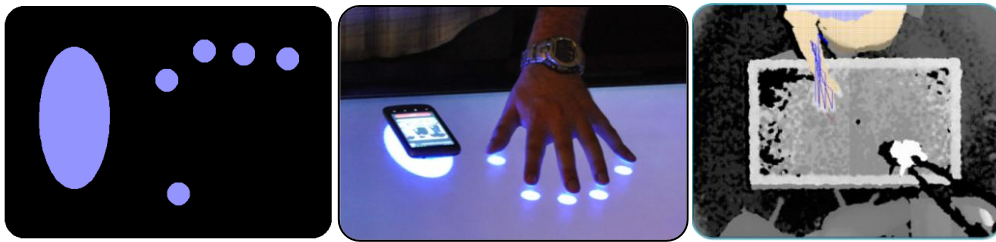


Figure A-10 Left and Centre: The tabletop distinguishing between fingers and devices. Right: Depth information captured by the overhead mounted sensor used to track hands and bodies above the surface.

The handshaking protocol is:

- 1 **Register the device with the application**  
*This is done by pressing the start button on the personal device (Figure 1). The device sends to the tabletop its unique hardware identifier.*
- 2 **Place the device on the tabletop**  
*The tabletop recognises a physical object, so it makes a coloured oval around the object and broadcasts to all registered devices – a handshaking request – which is the colour beneath the device. This is shown in the upper image of Figure 4.*
- 3 **The device sends back a colour.**  
*This is captured upon intercept of the handshaking request by the device's camera in the background.*
- 4 **The system fuses the sensor inputs together.**  
*The system uses the information to figure out which registered device was placed down, and links the identity with the appropriate tracker user. This is shown in Figure 7.*

Figure A-11 Handshaking protocol.

Provided that the personal device is connected to the tabletop it takes a short period for the device to be paired to a tracked user. Once a device has been identified and paired with a user, the system will continuously track the touches of the user even if the device is removed from the tabletop. In this case, the device need not be tied to the tabletop and can be used for other purposes, such as viewing personal content or selecting files to share with other users. Removing it from the table may also be desirable to avoid clutter, freeing up the interface for collaboration, or alternatively used as a private space.

### A.3.3. Example User View

We created a photo sharing application. It enables users to share photos that are on their phone at the tabletop. We illustrate a person using it in Figure A-12. The user places their phone on the tabletop. After the identification process described earlier, the phone loads appropriate data from its library as shown in Figure A-12 (left), where the phone has a yellow halo. When a person has been

<sup>1</sup> Kinect sensor device: <http://www.xbox.com/kinect>



detected, their touches are tracked and associated with them. Once the person has also been identified, the colour becomes a deeper coloured halo. The benefit of combining user identification and user tracking on a shared tabletop surface is that it permits the tabletop to become more aware of its users and to incorporate personal devices.

An example where this is useful is when two people walk up to a tabletop in a workplace meeting room. They each place their device on the tabletop. It identifies them, noticing they are working on the same project and as it is in a meeting room, automatically loads and makes accessible files and resources needed for an impromptu meeting. This could also facilitate multiple personas on the device – each representing a different role or profile for different projects a person works on.

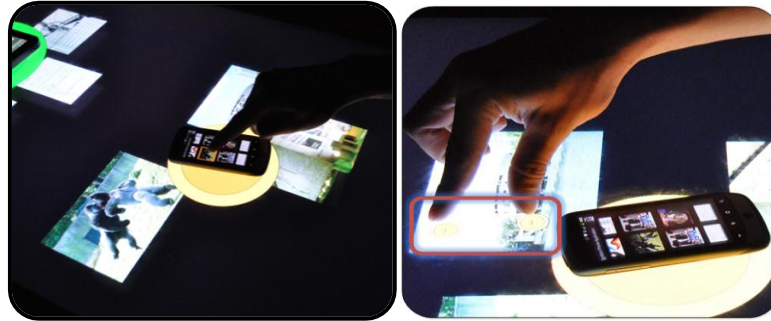


Figure A-12 Example user view.

The purpose of this prototype is to make the surface a digital environment that is aware of users' interactions with the tabletop, their physical disposition and their activity beyond the tabletop. The aim is to deliver services to users in the form of contextually aware interaction, personalised content or privacy mechanisms. For example, future research should consider privacy aspects. The user may be presented with a tiered privacy control when they walk up to a tabletop to use it with their private device. They can then share private material and ensure that only they can interact with it. In addition, if a device is removed from the tabletop, the system could automatically remove private content. There could also be mechanisms to leave less private material on the table until they move away from the table. This provides a mechanism to support privacy on shared surfaces.

## A.4. Learning Materials for the Studies in Chapter 8

### A.4.1. Foundations of Management: Learning Material for the Case



THE UNIVERSITY OF  
SYDNEY

## Work 2201 Foundations of Management Semester 1, 2012

### Managing power and politics

#### **Tutor Name: Maresa**

#### **Tutorial week 9**

Audrey, a 33 year old HR Specialist in a mid-sized information technology consulting company called I-Tech is faced with a dilemma. Audrey started working for I-Tech as a HR Generalist about 4 years ago. She has been promoted once, to her current role of HR Specialist, and her boss Tom, the HR Director, has privately suggested that if she keeps up the good work she will get promoted to Senior HR Specialist within the next few months. She has been working very hard for this promotion.

Following a staff meeting yesterday, Tom pulled Audrey aside and confidentially told her that, due to the financial difficulties the company was facing, HR would need to identify about 20 to 25 I-Tech staff for retrenchment. So far the CEO of the company had only told senior management, namely the CFO, the Marketing Director, the head of the IT specialists department, and Tom. The CEO made the decision quickly in response to pressure from the CFO to act fast and find a solution for their financial situation. The CFO himself was responding to pressure from the owner of the business, who had been shocked by the financial numbers when they were presented to him recently. Having been advised to act fast, the CEO decided that redundancies might be the quickest way to reduce costs in the company and therefore informed senior management. The CEO specified to senior managers that they would not be considered for redundancy, but that lower levels of the company will be considered.

Tom informed Audrey of the developments partly because he will be away during the important part of the process. Over the next few weeks Tom will be on a business trip, followed by some holidaying on annual leave with his wife of 15 years. This means that Audrey will be in charge of the most important parts of the process: reviewing everyone's past and current performance evaluations and selecting the 20 to 25 employees for senior management to consider for redundancy. According to Tom this is a great chance for Audrey to prove her managerial skills which are necessary for the promotion to Senior HR specialist.

Audrey's dilemma is that she is friends with most of the lower level staff as she had started as a generalist herself. Audrey never considered herself as a manager, but rather as one of the general staff members who are of a similar age. Her best work colleague, Joanne, is also her housemate and the two girls usually go for Friday after work drinks with some of their other colleagues. Audrey considers herself very lucky living with Joanne in a huge apartment as without Joanne's generous rent payment she could not afford to live there. At work Joanne has constantly underperformed in the past couple of years and has never met her performance targets. At the same time, Joanne has been involved in an affair with the HR Director Tom. Only Audrey and Tom's secretary know about this affair as they repeatedly had to make up plausible excuses to Tom's wife. Most of Audrey's work colleagues have either young families, have mortgage to pay, still owe on their HECS debt, and some have a combination of these pressures..

#### 1st exercise:

As a group of 4 to 6 students create a concept map explaining the relationships of all stakeholders involved while visualising the power dynamics and hierarchy of these actors. You have 15 minutes to complete this task. Possible concepts are already given, you don't have to use all of them if you don't want to and you can also create additional ones if you would like. There is also a given list of connection options that you can use indicating the relationships.

#### 2nd exercise:

In your groups have discussions on what options Audrey has in this situation and explain what you would do in her situation. You have to show your group decision visually in the concept map by changing the concepts depending on their power status, e.g. shifting Audrey further into the middle or out of the company. You can shift any concept depending on what your solution is, you can also create a new concept if you decide on e.g. involving trade unions or media etc. at the end of this exercise it has to be obvious how you would advise Audrey to act by specifying who is included in your concept map, their power status and their relationship connections. This exercise will take 15 minutes.

Remember as always when it comes to management theories, there is no right or wrong, it all depends on your discussions and what you as a group think is the best solution for this scenario.

### A.4.2. Foundations of Management: Suggested concepts and links

Concepts suggested by the teacher and displayed to students in the concepts menu:

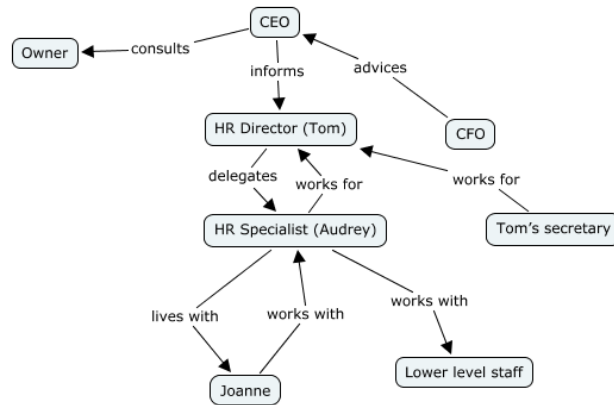
CEO	Tom	Senior Management	Work colleagues
HR Specialist	CFO	Lower level staff	Marketing Director
HR Director	Audrey	Head of IT department	Tom's wife
Owner	Joanne	Tom's secretary	I-Tech staff

Links suggested by the teacher and displayed to students when creating a proposition:

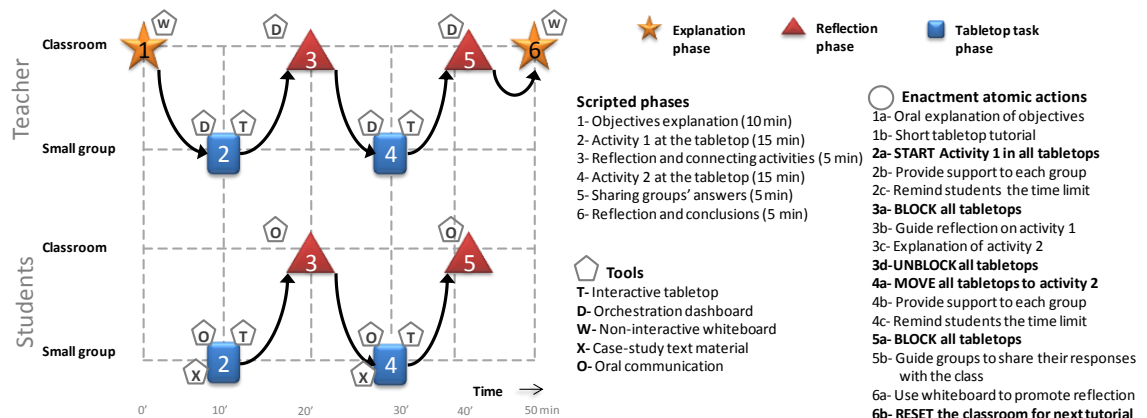
informs	advices	works for	is colleague
delegates	reports to		

### A.4.3. Foundations of Management: Master map

Concept map created by the teacher before the classroom sessions. It contains the crucial propositions and concepts that should be included.



### A.4.4. Foundations of Management: Classroom Script



#### A.4.5. Organisational Ethics: Learning Material for the Case



### **Work 2219 Management and Organisational Ethics Semester 2, 2012**

#### **Ethics and the employee**

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*Tutor Name: Maresa*

*Tutorial week 6*

ComTech is a multinational corporation operating in 9 countries worldwide. With over 5,000 employees ComTech offers IT services including programming, software maintenance, technical support and advisory. On the Monday the 23<sup>rd</sup> of August 2012 an email was circulated by Jack, a computer software technician, to all employees within ComTech. The email contained a sexist joke against women with the joke's leading character called 'Sally'.

Jack, the sender of the email, is known by his friends and close colleagues to be a funny person whose jokes are, at times, clumsy and easily misinterpreted. Sally, the administrative officer of the Company, read the email and thought the joke was about her. This made her furious. She felt sexually discriminated by her colleague and she went straight to the HR department to complain. During her conversation with Wayne, the HR director of ComTech, she emphasised her rights as an employee to be treated fairly and with respect by everybody and that an email like that is unacceptable. Following the conversation with the HR director, Sally's demands to HR were the following:

- Jack needs to publicly apologise to her in the next departmental meeting and send the same apology email to all ComTech employees.
- HR needs to take legal action to discipline Jack for his behaviour.
- HR needs to create a new HR policy stating that this sort of behaviour will result in immediate dismissal.

If those demands are not fulfilled by HR, she will take legal action against the company and go public with the situation. Wayne gives Dave, a HR representative, the task to sort the situation out. Dave is told by Wayne to make sure that Sally does not take legal actions or inform the media. Instead the strict order from Wayne is that Dave should make sure that Sally accepts some money from the company as compensation for her suffering. Wayne makes himself very clear that if Dave does not do 'his job' he will no longer be part of the company.

Louise, the middle manager in the HR department and Dave's manager overheard Wayne's instructions. Louise firmly disagrees with the approach suggested by Wayne. Louise and Wayne had an affair and Louise is yet not over the disappointment that Wayne did not leave his wife for her. Wayne instead ended the affair with Louise after six months. Louise, still

disgruntled, decides that it is payback time. Louise calls Dave in to her office and tells him to dismiss both Jack and Sally for their childish and unacceptable behaviour; Jack for sending the email and Sally for trying to blackmail the company. Louise tells Dave that if he fails to dismiss them both, she will give him a negative performance appraisal evaluation. This will likely prevent Dave from any promotions in the near future. Dave feels helpless and does not know what to do!

1st exercise:

In a group of 4 to 6 students continue developing a concept map that is already given to you. Explain the relationships of all stakeholders involved and highlight the various ethical dilemmas employees are in. You have 10 minutes to complete this task.

2nd exercise:

In your groups have discussions on what options Dave has in this situation and explain what you would do in his situation. You have to show your group decision visually in the concept map by changing the concepts and their relationships depending on what you think is the best solution for Dave. Keep in mind that there are various ethical dilemmas in this case and that different solutions implicate different outcomes. You can shift any concept depending on what your solution is, and you can also create a new concept if you decide on e.g. involving trade unions or media etc. At the end of this exercise it has to be obvious how you would advice Dave to act by specifying who is included in your concept map and their relationship connections. This exercise will take 20 minutes.

Remember as always when it comes to ethics theories, there is no right or wrong, it all depends on your discussions and what you as a group think is the best solution for this particular scenario.

## A.4.6. Organisational Ethics: Suggested concepts and links

Concepts suggested by the teacher and displayed to students in the concepts menu:

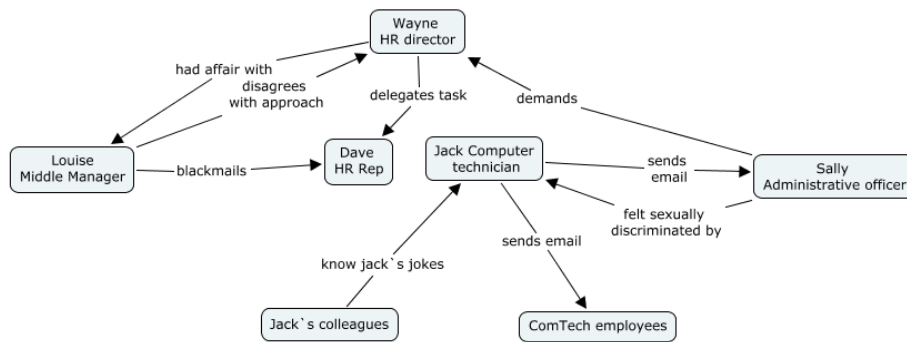
Sally Administrative officer	Union	Wayne HR Director
Jack Computer technician	Whistle blowing	Dave HR Rep
ComTech employees	Media	Legal action
Louise Middle manager	Wayne`s wife	Department meeting
HR policy	Promotion	Jack`s colleagues
Product prices*	Technology*	

\*Only available after the first activity is finished.

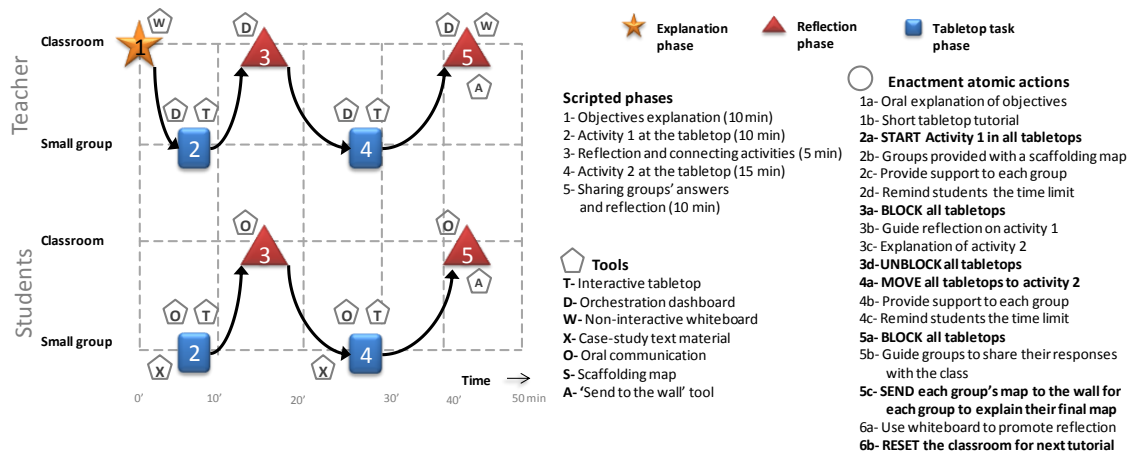
Links suggested by the teacher and displayed to students when creating a proposition:

works with	sends email	works with	works with
is threatened by	dismisses		

## A.4.7. Organisational Ethics: Master map



## A.4.8. Organisational Ethics: Classroom Script



## A.4.9. Organisational Ethics: Initial scaffolding map at the tabletop

