RECOMMENDATIONS FOR THE SELECTION OF METHODS FOR THE ANALYSIS OF ECOLLABORATION BASED ON A SYSTEMATIC LITERATURE REVIEW

Research paper

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Abstract

Learning Analytics plays an increasing role in the analysis of virtual learning activities. This article addresses the gap between educational needs and technical supply. By means of a Systematic Literature Review of the LAK conferences the authors extracted observations, methods and tools which represent potential solutions for a given eCollaboration scenario. Based on three prioritised examples of an observation sheet, methods are derived and recommendations for the use of Learning Analytics tools are given. The result is a catalogue that enable users to select suitable methods and tools for an implementation. The (semi-) automation can increase the efficiency of Community Managers in monitoring the participants and hence make real-time intervention feasible.

Keywords: Learning Analytics, eCollaboration, Virtual Collaborative Learning, Community Manager

1 Introduction

A future trend of education lies in the virtual classroom, because the augmenting number of people in training and further education, will decreasingly be addressed via conventional educational pathways (Johnson, L., Smith, R., Willis, H., Levine, A. und Haywood, K., 2011). For example, the amount of activities in virtual space has been increasing for years (Bratengeyer et al., 2016) and new methods are needed to be able to handle the increasing number of student data as well as to adequately support individuals (Bakharia and Dawson, 2011). Since 2011, Learning Analytics has been addressed as a novel method for evaluating this data in Horizon Reports (Johnson, L., Smith, R., Willis, H., Levine, A. und Haywood, K., 2011). In the course of this development, Learning Analytics has meanwhile grown to become a frequently discussed research topic on various platforms and has also arrived in practice (Siemens, 2012). One objective is to design solutions for student learning communities (Ferguson and Shum, 2012) with Social Learning Analytics.

The starting point of this paper is a "Virtual Collaborative Learning" (VCL) setting in which eCollaboration serves as a central learning objective and simultaneously as a mean for other learning objectives. With the help of Social Software, small groups of students with up to six members have to work together on various complex case studies in a virtual environment within about six weeks (Balázs, 2005). Since students are often uncomfortable with this unusual form of group work, specially trained Community Managers ensure that the learning objectives are achieved. They passively participate as contact personnel, monitor community processes and intervene pro- and reactively if necessary (Rietze and Hetmank, 2016). However, the prerequisite for this is the correct and timely provision of information. The available observation sheet must be continuously processed and the status of the group work must be documented. Due to its size, however, it is hardly possible to observe the data in real time by hand. Another obstacle is the use of the various (decentralised) tools, which makes it difficult to track activities and their holistic interpretation. If some activities are ignored by or invisible for the Community Manager, the characteristics of the group activity are not recognized in real-time and problems become apparent only with a delay. If observations have to be done manually, Learning Analytics offer the possibility to improve efficiency and effectiveness.

In previous contributions, it was investigated which elements of the observation of eCollaboration are particularly relevant for the tracing of community activities (Rietze, 2016a). Based on this prioritization, these observations were analysed in more detail (Rietze, 2016b) in order to gain a more comprehensive understanding. However, so far there has been no combination of these educational goals with the existing approaches to designed methods or tools of computer scientists. This leaves a gap that prevents the demand-oriented implementation of Learning Analytics. This article addresses this gap and links the two disciplines by identifying potentially suitable methods for selected examples of this observation sheet and systematizing them as part of a catalogue for Learning Analytics of eCollaboration. At the same time, the examples show the procedure and offer recommendations for a prototypical implementation.

2 Research design

This article was written as part of a comprehensive Learning Analytics research at the Chair of Wirtschaftsinformatik – Informationsmanagement of the TU Dresden. For a collaborative teaching and learning approach, we investigate how the data on the activities of the participants that are available to the Community Manager can be prepared according to their needs.

This article develops a catalogue in which established Learning Analytics methods are selected for the analysis of eCollaboration for 3 high prioritised observations (e. g. Rietze, 2016b, 2016a). Three research questions were formulated as the basis of the procedure:

- How can eCollaboration be analysed?
- Which methods can be used to evaluate observations made by the Community Manager?
- Which tools exist to analyse eCollaboration?

A Systematic Literature Review (Fettke, 2006) is conducted to collect this information. To this end, the publications of all Learning Analytics and Knowledge conferences (LAK) from 2011 (first time) to 2017 (last time) will be filtered with regard to their reference to eCollaboration and examined for applied methods and analysis tools. The conference was chosen because it represents the results of the leading international scientists in the field of learning analytics. The columns of Table 1 show the distribution of the selected publications on the respective conferences of the LAK. The rows represent the selection procedure.

	LAK11	LAK12	LAK13	LAK14	LAK15	LAK16	LAK17
$N=489$	27	52	47	55	84	98	126
$n_{coll}=148$	14	26	24	20	34	39	43
$n_{corr}=109$	11	19	12	9	18	22	18
$n_{final}=89$	8	16	11	8	14	17	15

Table 1. Selected papers of the LAK conferences

The total number of all publications (N=489) was automatically preselected by means of the data fields *Title*, *Abstract* and *Keywords* by using the following terms for virtual group work: *network, connectiv, social, communit, collaborat, cooperat, cscw, cscl, chat, forum, wiki, blog, twitter, facebook*. The remaining publications (n_{coll}=148) thus thematise collaboration, whereby the authors assume a synonymous use of the terms cooperation and collaboration.

In a second selection step, the same data fields were searched manually and contributions to Academic Analytics, cross-course and general Learning Analytics were removed. As a result, publications are now included that contain methods and tools used, information on analysed data or explicit observations within a course. After this manual correction, n_{corr}=109 publications remained for the subsequent full text analysis.

During the full text analysis, it was possible to extract information from n_{final}=89 publications on the observations, the applied methods and analysis criteria as well as existing Learning Analytics tools. Extracting the evaluation criteria for collaboration was challenging, because in most cases this was not the actual research goal. Therefore, evaluation and observation criteria had to be identified or reformulated by the authors.

Based on these findings, the research questions will be answered successively in the upcoming chapters. First, the identified Learning Analytics methods for analysing eCollaboration will be pointed out. Subsequently, three observations of the Community Manager are described, to which potentially suitable analysis methods are assigned. Finally, Learning Analytics tools are named which can be used at an implementation. The contribution thus integrates the key work for specialised researchers from the field of Learning Analytics and eCollaboration (Fettke, 2006).

3 Catalogue for Learning Analytics and eCollaboration

To address the gap between demand and supply, the authors first provide an overview of Learning Analytics methods that can be used in eCollaboration. Important observations to which suitable methods are assigned are listed below.

3.1 Methods for Learning Analytics

This chapter addresses the first research question and answers which methods can be used to analyse eCollaboration. Within the framework of the evaluated literature, 46 methods were extracted and classified into four method groups: *Network Analysis*, *Statistics*, *Content Analysis* and *Discourse Analysis*. These methods are grouped according to the classification of Ferguson and Shum (2012) with the extension of the statistics. For a better understanding of their characteristics, these groups are visualised in Figure 1 in the field of conflict between quantitative and qualitative analysis.

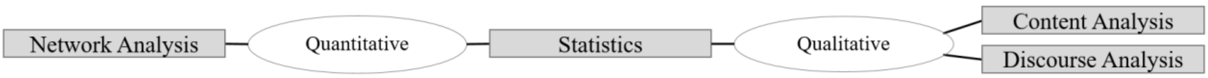

Figure 1. Classification of method groups

With 63 applications, Network Analysis is the most widely used method group in the contributions examined. In this group, the method of Social Network Analysis (SNA) with a frequency of 30 is the dominant method. The group was deliberately not called SNA, as several methods do not include the social point of view, but examine all kinds of structures. This group combines methods that can identify structures and create relationship analyses with the help of networks and graphs. In terms of content, there is a further focus on recognizing and visualizing the progress of interactions in a group and between individuals. Furthermore, key figures can be identified and the benefits of interactions within the group can be evaluated. Moreover redundant or isolated parts of a community can be identified (Bergner et al., 2017).

The following 15 methods have been grouped under Network Analysis: *social network analysis, network visualization, visual analytics, graph based node, link visualization, main path analysis, temporal analysis, socio-semantic block modelling, block modelling, network analysis, network directed graph, contingency graph, adjacency matrix, generalized interaction model, associogram, user profiling, domain modelling*

In the middle of the two categories of the diagram, the Statistics are to be classified, as they are always quantitative in their analysis due to their mathematical origin. Within the framework of Learning Analytics, however, statistical methods are also used for a large number of qualitative evaluations. For example, methods such as clustering (Joksimović et al., 2015; Lee and Tan, 2017; Suthers, 2015) and classification (Bergner et al., 2017; Wise et al., 2016) group and summarize topics in terms of their content. As a result, Statistics are significantly represented in the Learning Analytics with a frequency of 47 due to the diverse use of its subordinate methods.

The following 18 methods have been grouped in Statistics: *Descriptive statistics, clustering, classification, statistical discourse analysis, support vector machines, automatic post classification, machine learning, gaze analytics, locally linear embedding, exploratory sequential data analysis, regression analysis, time series analysis, user knowledge modelling, concept classification, computational linguistics, multimodal analytics, trend analysis, frequency analysis*

The third method group Discourse Analysis can be classified in the qualitative category and, with about a frequency of 35, is much rarer than SNA. Its focus is on content and interpersonal group interaction based on the language used. Questions about the participants' performance and central topics in the discourse can be answered with this method group. Furthermore, the settings of the subscribers can also be determined (Ferguson and Shum, 2012; Bergner et al., 2017).

The following nine methods have been grouped under Discourse Analysis: *Natural Language Processing, discourse unit network, latent semantic analysis, latent semantic indexing, ethnography, relationship mining, sentiment analysis, revision map*

Content Analysis was the least represented method group with nine entries and can also be classified in the qualitative category. In this context, the focus is on the observation of the content generated by the learner. The aim here is to recognize content-related patterns in communication (Bergner et al., 2017). However, the scientific contributions showed that there are different ideas for content analysis and that it is defined as a broad field of methods (Cukurova et al., 2016).

The following 4 methods have been grouped under Content Analysis: *Latent dirichlet allocation, text mining, topic modelling, disposition analytics*

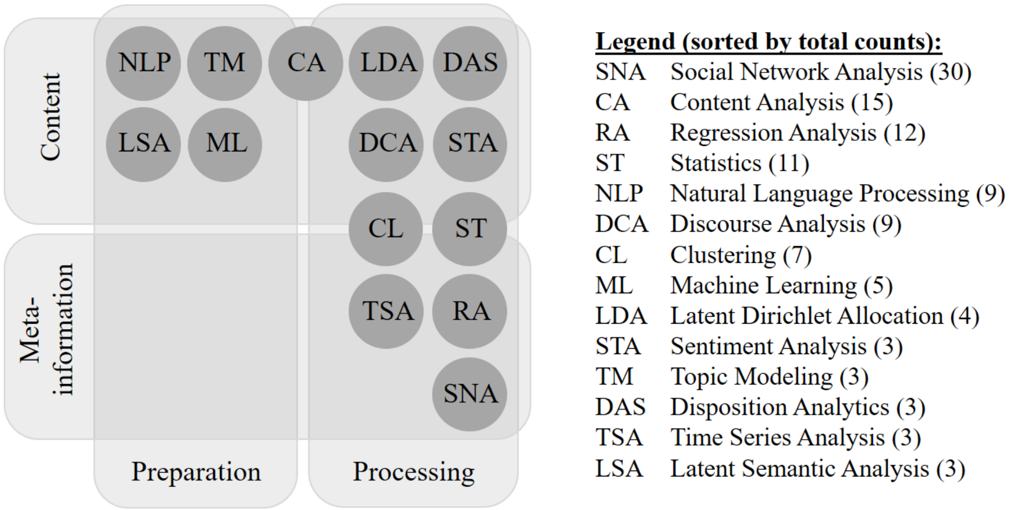

Figure 2. Classification of methods into data type and phase of analysis

In Figure 2, a classification of the methods is visualized with the two dimensions of the data type (*Metainformation* and *Content)*, as well as the phase of analysis (*Preparation* and *Processing)*. The distinction between *Content* and *Metainformation* shows how structured the data to be analysed is. The dimension *Preparation* and *Processing* clarifies which methods are used to transform and edit the data and which methods are used for the actual analysis. The circles shown in the diagram represent the respective methods. These are arranged in the respective quadrants, whereby the size of the circles does not indicate the frequency. The authors intentionally ignored this further detail since the differences in frequency would have been too great to visualise effectively. The position in the quadrant is not considered differentiated, due to the different possibilities according to the design and use of the method. In the context of this classification, it is noticeable that the left lower quadrant remains empty, since *Metainformation* is already available in a structured form and therefore no method of *Preparation* is necessary. The frequency with which the respective method is represented can be found in the legend. For better readability, only methods that have been used at least three times are shown.

3.2 Observations of eCollaboration

The analysis needs of the VCL projects were investigated in previous studies. On the one hand, the various observation forms in use were homogenized and on the other hand, individual observations were prioritized with regard to relevance and complexity. This resulted in a better understanding of *WHAT* should be observed and evaluated (Rietze, 2016a). Subsequently, the high-priority observations were analysed for specific criteria and data to gain knowledge of *HOW* and *WHICH* data has to be evaluated (Rietze, 2016b).

The observation sheet is divided into observations of the process and the product. Within the framework of the process observations, it is monitored how the participants communicate with each other and how they collaborate or cooperate. These observations are primarily used by the Community Manager to intervene in case of problems concerning the cooperation. The observation of the product is used to assess the result, including the submission of subtasks. In this way, the Community Manager can also get an idea of the quality of the products during the processing period and, if necessary, intervene in order to influence the following subtasks and the overall product (Rietze and Hetmank, 2016). Within the scope of this article, three high-priority observations from the areas of communication, collaboration/cooperation and product will be evaluated.

3.3 Methods for the observations

The VCL projects have been introduced as an application case with the relevant observations and potential Learning Analytics methods have been identified. Now suitable methods are to be assigned to the specific observations. This chapter thus addresses the research question 2, focussing on which methods can evaluate which VCL observations.

The basis for this classification is the applied Systematic Literature Research. For this purpose, the selected publications were analysed for their observations and fitting references were transferred to the VCL projects. The explanations in the publications had different levels of abstraction. Concrete observations of the literature research serve as criteria for the observations of the VCL on the basic level. In a more abstract form, they can be used non-specifically for several observations of the VCL. Similarly, in some publications causalities were examined that are not in themselves relevant for the observations in the context described here. However, it was possible that within the framework of data collection or processing in these publications, individual methods provided an insight for observation.

The following table picks up the C4 observation from the communication part of the observation sheet. With reference to the criteria described in the previous chapter, the observations are listed and the methods are derived from them. It can be noted that SNA and statistics are often used for these cognitive goals, so prototypical implementations should prefer these two methods.

Cognitive Goals	**Methods**	**References**
grouping of activities/ participants	Clustering	(Ezen-Can et al., 2015; Xing et al., 2014)
history of activities	SNA	(Halatchliyski et al., 2013)
interconnection vs. isolation; frequency of interactions, comments and answers; read-/write-access within a group; pro- vs. reactivity	SNA	(Bakharia and Dawson, 2011; Bieke and Maarten, 2012; Cambridge and Perez-Lopez, 2012; Liddo et al., 2011; Paredes and Chung, 2012; Schreurs et al., 2013; Suthers, 2015; Lee and Tan, 2017; Vatrapu et al., 2011; Rahman and Dron, 2012; Joksimovi et al., 2016; Boroujeni et al., 2017; Wise et al., 2017; Fournier et al., 2011; Koh et al., 2016; Poquet et al., 2017; Zhu et al., 2016)
frequency of logins, read-/write-access; comments, likes	Statistics	(Suthers, 2015; Rahman and Dron, 2012; Fournier et al., 2011; Santos et al., 2014; Clow and Makriyannis, 2011)
development of activities over time	Time Series Analysis	(Lee and Tan, 2017)

Table 2. (C4) Is the participant also acting asynchronously?

The subject of observation T11 is controlling of the completeness of the task and their timely execution. The following table shows that observations can be gained through a wide selection of methods without a method having been applied particularly frequently.

Cognitive Goals	Methods	References
activitiy of the participants	Content Analysis	(Suthers, 2015; Fournier et al., 2011)
	Discourse Analysis	(Fournier et al., 2011)
	SNA	(Suthers, 2015; Halatchliyski et al., 2013)
	Statistics	(Suthers, 2015; Rahman and Dron, 2012; Vozniuk et al., 2014)
development of the sessions	Content Analysis	(Suthers, 2015; Fournier et al., 2011; Gunnarsson and Alterman, 2013)
	Statistics	(Suthers, 2015; Rahman and Dron, 2012; Vozniuk et al., 2014)
	Regression Analysis	(Pijeira-Diaz et al., 2016)
relevance of the posts	Content Analysis	(Suthers, 2015; Fournier et al., 2011)
	SNA	(Vatrapu et al., 2011)

Table 3. (T11) Are all tasks carried out completely?

A detailed and conclusive description of the group contract supports the handling of group tasks and prevents problems. The group formulates this contract before starting an assignment. The following table shows that the gain in observations related to the study of the group contract is described in the literature by using different methods. Again, there is no significant accumulation of a specific method.

Cognitive Goals	Methods	References
activity of a participant	SNA	(Halatchliyski et al., 2013)
activity within a group	Discourse Analysis	(Southavilay et al., 2013)
	SNA	(Southavilay et al., 2013)
	Topic Modeling	(Southavilay et al., 2013)
quality of posts	Regression Analysis	(Pijeira-Diaz et al., 2016)
	Statistics	(Vozniuk et al., 2014)
relevance of posts	Statistics	(Vozniuk et al., 2014)
	SNA	(Vatrapu et al., 2011)
presence of norms and agreements	SNA	(McAuley et al., 2012)

Table 4. (R33) Is the group contract written detailed and coherent?

The tables above have shown the allocation of Learning Analytics methods to the exemplary observations for eCollaboration. By interconnecting these both topics, the authors have reduced the identified gap between teachers' needs and IT solutions. Now, these tables enable users to select the methods relevant for their observation or doing further analyses for other observations by applying such a procedure. The next chapter summarises the results and lists tools that can be used to implement Learning Analytics.

3.4 Tools for Learning Analytics methods regarding eCollaboration

In the course of this chapter, tools that are suitable for implementation Learning Analytics are assigned to the methods discussed so far. Table 5 describes the results of the Literature Research and thus only includes tools that are used in the eCollaboration settings. There is no further consideration of the functionalities of the individual tools. So that the table can provide a reference to eCollaboration, but does not guarantee the completeness of the functionality of the individual tools.

Tools / Methods	Network Analysis	Statistics	Content Analysis	Discourse Analysis
SNAPP, NodeXL, Netdraw, KBDeX, VASCROLL, NAT, Cytoscape, Sonivis, SocNetV, SNA-network, Wikiglass, Vizster	X			
LASSIE	X	X		
LearnB, SPARK, CLA, Google Analytics		X		
Gephi, R	X	X	X	
UCINET	X		X	
Jung, Palek, LOCO-Analyst			X	
Cohere, iStart, ReaderBench, TAALES, TAACO, SEANCE, WAT				X

Table 5. Tools of Learning Analytics for method groups for eCollaboration

The classification is based on publications describing and analysing both methods and tools. However, this is only a subset of publications as a large number of them use or analyse methods or tools, but not both. Furthermore, only the more numerous representatives are summarized here. Only assignments that have been linked more than five times are shown. Mentions with a lower frequency, such as e.g. self-developments are not included in the table for the sake of clarity.

4 Conclusion

This paper addresses the application of Learning Analytics in the field of eCollaboration courses. Based on a concrete course setting, observations of Community Managers were explicated and suitable methods and tools were chosen to measure them. The basis of the Systematic Literature Review is all papers of the LAK referring to eCollaboration. The intended observations, the methods and the tools used were extracted and transferred to selected observations of the underlying application case. The results are an overview of Learning Analytics methods that can be used to measure eCollaboration and furthermore a list of corresponding analysis tools.

Regarding the results and the conclusions drawn from them, the selection criteria for this Systematic Literature Review must be critically assessed. This article is limited exclusively to the LAK as the world's leading conference in the field of Learning Analytics. Other publication platforms, contributions in languages other than English, and related areas such as Educational Data Mining were not considered. Furthermore, evaluating the established catalogue with regard to the requirements of Community Manager in accordance with the Design Science paradigm (Hevner, 2007) and adapting the catalogue accordingly are the next steps, which need to be taken in this research path. The results can further be compared and extended with other sources.

With this contribution, the authors were able to reduce the gap between the educational requirements arising from the observations made by the Community Manager and the methods and tools used in computer science to measure and analyse these observations. Moreover, this paper points out an approach as well as develops an exemplary catalogue that can be used as a part of a guideline for the implementation of Learning Analytics in eCollaboration courses.

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