Contextualising Learning Analytics with Classroom Observations: a Case Study

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Abstract. Educational processes take place in physical and digital places. To analyse educational processes, Learning Analytics (LA) enable data collection from the digital learning context. At the same time, to gain more insights, the LA data can be complemented with the data coming from physical spaces enabling Multimodal Learning Analytics (MMLA). To interpret this data, theoretical grounding or contextual information is needed. Learning designs (LDs) can be used for contextualisation, however, in authentic scenarios the availability of machine-readable LD is scarce. We argue that Classroom Observations (COs), traditionally used to understand educational processes taking place in physical space, can provide the missing context and complement the data from the co-located classrooms. This paper reports on a co-design case study from an authentic scenario that used CO to make sense of the digital traces. In this paper we posit that the development of MMLA approaches can benefit from co-design methodologies; through the involvement of the end-users (project managers) in the loop, we illustrate how these data sources can be systematically integrated and analysed to better understand the use of digital resources. Results indicate that CO can drive sense-making of LA data where predefined LD is not available. Furthermore, CO can support layered contextualisation depending on research design, rigour and systematic documentation/data collection efforts. Also, co-designing the MMLA solution with the end-users proved to be a useful approach.

Keywords: Classroom Observations, Learning Analytics, Multimodal Learning Analytics, Blended Learning, Co-located Classrooms, Contextualisation, Learning Design

1 Introduction

Teaching and learning processes increasingly take place in blended learning settings and in both, physical and digital spaces. While Learning Analytics (LA) solutions offer automated means to collect and analyse digital traces, they only provide a partial view of the whole picture. To cover this gap, the subfield of Multimodal Learning

Analytics (MMLA) integrates evidence from the physical spaces using other automated means such as sensors, EEG devices, eye tracking, etc. Despite it, to make sense of those datasets, pedagogical grounding and/or contextual information may still be needed [1]. Researchers suggest using learning design (LD) to contextualise the analysis [2]. However, practitioners do not always produce digital versions of the scripts or LD that can be automatically interpreted due to technological or LD adoption challenges [3]. Alternatively, classroom observations have been used in authentic scenarios to understand educational practices taking place in the physical space, providing additional and highly contextual information with other data sources [4][5][6]. Aside from the abovementioned issues, the complex process of embedding innovation in authentic contexts was viewed as challenges related to human factors [7], and the co-design methodology to involve the user in the development of LA solutions is one way to respond to adoption challenges [8].

This paper reports on a case study in which researchers and end-users co-designed an MMLA solution where classroom observations were used in combination with digital traces to better understand the adoption of digital learning resources in authentic learning scenarios. We argue that, in co-located classrooms, systematic CO can help to understand the context where the digital traces took place in authentic, real-life scenarios. Moreover, a co-design methodology can help address adoption issues referred to in previous research, by co-designing the MMLA solution with end-users.

2 Making Sense of Learning Analytics: context and design-aware observations

LA is a rapidly developing field of research and practice that seeks to analyse learning processes and their context to optimize, support, challenge and reshape educational practices [9]. Inherently, it focuses mainly on the data collected through digital means, providing a strategic way to understand how digital tools are used. However, in blended learning, without knowing the context where the digital artefacts were used, it sometimes is difficult to make sense of the available data [2]. To contribute to the LA sense-making, different solutions have been proposed in the literature; When the learning theories or the pedagogical approach are known, some authors have suggested adopting theory-driven approaches to obtain meaningful analytics [10, 11]. However, it does not guarantee that the interpretation of the data fits the reality of the learning context.

Other researchers have proposed that the use of LDs can contribute to the contextualisation of data analysis [2][12]. While the benefits of using the LD to guide the data analyses have been reported by many authors, access to such design represents one of the main challenges [13]. Frequently, due to time constraints practitioners may not even document their lessons plans [14]. In some other cases, the LD may be collected in a format that is not automatically interpretable (e.g., using hand-written diagrams, schemes, or lists of steps). In the optimal but less frequent scenario [2, 15], the practitioners may have registered their designs in an authoring tool. However, even in this case, the interoperability with the tool is not guaranteed since there is no single data format to represent the LD [16].

A different method used to understand learning processes or situations is classroom observations [17]. While some data collection methods (such as surveys or interviews) target participant views, classroom observations can provide a non-judgmental description of learning events [18]. CO can gather data on individual behaviours, interactions, or the physical setting by watching *behaviour*, *events*, *artefacts* or noting *physical characteristics* [17]. Observation types may vary on the continuum from unstructured, semi-structured to structured (systematic). This means that unstructured observations produce qualitative data and structured observations – quantitative [19]. Some authors argue that CO benefits from qualitative and unstructured data gathering [17], others advise against it since it may result in big volumes of unstructured data [20]. On the contrary, while reducing expressivity, systematic (structured) observations allow for more efficient analysis and data processing [21]. Therefore, systematic observations are especially suitable to be combined with digital traces, enriching each other to understand learning processes and contexts with the help of multimodal learning analytics [22].

Traditional classroom observations require human inference and are highly contextual; human-mediated labelling is often used in MMLA to relate raw data to more abstract constructs [23][24]. Observation data integration with LA can happen for triangulation purposes [25], for observing technology-enhanced learning [26], inferring meaningful learning interaction data through annotations of direct observations [27] and video annotation to triangulate multimodal datasets, extract learning context and segment into time intervals has also been suggested [24]. Computer-assisted observation can help the process of observations through enforcing specific coding schemes and prevent missing data, speeding up the process of observations [28], enhance the validity and reliability of data [29]. Computer-assisted systematic observation tools have been suggested for recording interactions to study social dynamics at work [30], to annotate emotions from audio and video for multimodal analysis [31], to study student emotion and behaviour [29] etc. Most of the abovementioned tools are based on specific coding protocols or specific dimension of data (for instance, emotions) or theories (social dynamics), with little flexibility for developing own coding schemes that may not cater different research needs, cannot be guided by LD or/and may not be useful for contextualisation of data analysis.

Some authors [32] classify data according to whether collection and interpretation require human involvement or not. While digital traces could be easily collectable through automatic means, higher-level interactions taking place in the physical space may be more challenging to detect and record in the computational format. Thus, observers can contribute to sense-making, especially when data comes totally or partially from physical spaces [33].

Considering the aforementioned information, based on the lessons learned from previous studies [12][22], we have proposed the *Context-aware Multimodal Learning Analytics Taxonomy* (Fig. 1)[34]. The taxonomy classifies different research designs depending on how systematic the documentation of the learning design and the data collection have been:

Ideal - Systematic documentation and data collection: In the most desirable case, the learning design (including actors, roles, resources, activities, timeline, and learning objectives) is set up-front and documented in an authoring tool (e.g., LePlanner[1] or WebCollage[2]). Then, during the enactment, logs are collected automatically from the digital space and systematic observations from the physical one. During the enactment, the lesson structure is also inferred through observations. To ensure the interoperability, actors and objects need to be identifiable (across the learning design, logs and observations) and timestamps for each event need to be registered [35] Once the data is aggregated in a multimodal dataset, further analysis can be executed.

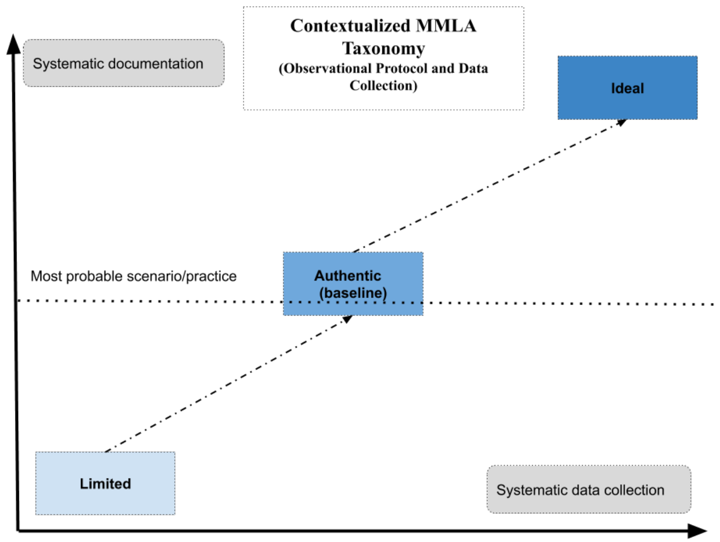

Fig. 1. Context-aware MMLA taxonomy

Authentic (baseline) - Non-systematic documentation but systematic data collection: We regard this level as a compromise between the limitations of authentic settings but still rich in terms of data. Here, the predefined learning design cannot be automatically used to guide the analysis (either because of its format or because it is not available). However, the timestamped lesson structure is inferred by the observer. Therefore, the actors are not identifiable across observations and digital traces. Nevertheless, both structured observations and logs are systematically gathered and collected in the Learning Record Store using a common format (e.g., xAPI). These conditions will enable the application of contextualised analysis on a more baseline level, using multimodal analytics.

Limited - Non-systematic documentation or data collection: Data collection happens non-systematically. As in the previous case, no information about the learning design is available (i.e., actors are not known). In terms of the design of the data collection, the protocol with corresponding codes may not be predefined, and semi-structured (non-systematic) observations are used. Thus, even if logs are systematical-

[1] https://leplanner.ee

[2] https://www.gsic.uva.es/webcollage/

ly gathered, the lack of systematisation of the observations hinder the application of multimodal data analysis. Although this is not an advisable scenario, logs and observations can be analysed independently and still provide an overview of what happened in the physical and digital planes. Besides, even if observations are done systematically, if the vocabulary (actors, objects and actions) are not agreed across datasets, then the potential of the multimodal analysis could be limited.

According to some authors, in many fields, the design of the data collection tools are not discussed, this is especially true in the field of observations [36]. Bearing in mind the constraints that LD-aware analysis may entail, we hypothesize that focusing on *the baseline scenario* case will help us to study and better understand authentic scenarios in non-experimental settings, without ad-hoc tools, where such innovations most probably will be applied. We argue that the development of such innovations through the involvement of the *"user in the loop"* and research-based design process is important. In the following sections, through a case study involving a participatory approach, we illustrate the feasibility of using observations to contextualise the data analysis in an authentic scenario involving the users in the analysis and interpretation data. We argue that, providing the alternative of using observations when the design is not available, more authentic scenarios will benefit from contextualised MMLA solutions. Moreover, through the suggested user involvement in authentic settings, we extract recommendations for the future development of MMLA solutions.

3 Research methodology and research questions

The overarching methodology of this research is a research-based design process that relies on the co-design of innovation though participatory approaches and stems from design-based research [37]. The stages of research are as follows: *contextual inquiry, participatory design, product design,* and *production of software prototype as a hypothesis*. These stages are not strictly separated and the research methodology suggests iteratively alternating between stages. Three stages were covered in the previous works: contextual inquiry, participatory design, and product design [12, 38–41]. This phase partly goes back to contextual inquiry and product design while also presenting the *software prototype as a hypothesis*.

The main goal of this research is to better understand *how MMLA can benefit from classroom observations* and *what is the value that observations may have for the sense-making of digital traces gathered from authentic context across physical and digital spaces*. Therefore, the main research questions addressed in the study are:

RQ1: Which aspects of digital-trace based LA could benefit from observations?
RQ2: What is the added value that Observations offer to the user in terms of meaning, context and quality?

Development and adoption of MMLA solutions that can be used in real-life situations is a highly complex process and human factors are to be taken into account [42]. To explore the feasibility of using observations for contextualisation of data analysis and analysis in authentic settings, as well as to gain a deeper understanding of sense-making processes and alleviate adoption issues, we employ the case study methodology *"to examine the instance in action"* [43] by progressively involving users in a co-design process. To reach this goal we followed a specifically developed method for the design of MMLA solutions, that entails *involving the end-users in the loop* [8]. This method defines four steps for the co-design of MMLA solutions: a) Understanding the MMLA solution. b) Definition of the questions to be asked by the MMLA solution. c) Reflection about the contextual constraints and the MMLA affordances. d) Refinement of the scenario and customisation of the MMLA solution.

Two project managers were involved in the co-design and evaluation of an MMLA solution. The study is framed within the Digiõpevaramu[3] project, where the main goal was to better understand how digital learning resources were used in the classroom. To achieve this goal, observations and logs from five lessons were analysed, also involving visualisation techniques. The study spanned for two iteration. The first iteration was mainly exploratory. Focusing on a single lesson, exploratory data analysis was carried out to identify indicators and visualisations that could be of interest for the project managers. Based on the lessons learnt, in the second iteration, the analysis of all five lessons was presented to the project managers to gain further insights about the customisation of the MMLA solution. During this process, mediated through data analysis, semi-structured questionnaires and interviews (1 interview per iterations) helped us gather feedback from the users on the further customisation of the MMLA solution. Questionnaire and interview data were analysed with content analysis method and are presented in section 4.4.

4 Case study

a. Context of the study

The study was conducted within the project Digiõpevaramu. Task-based [44] digital materials were co-developed together by the teachers and university experts, and 6000 digital learning resources were made available through an Estonian national level aggregator. Teachers could re-use the resources and mix different tasks into a collection to be used in the classroom. Materials were piloted in spring 2018 with 50 teachers and 1200 students from different types of Estonian secondary schools. While the project collects logs about the usage of the digital materials, this information was insufficient to understand how those materials were integrated into the teaching practice. Therefore, observers attended several lessons to collect evidence about classroom practice.

The case study involved 2 managers of the project who wanted *to understand how the digital materials were used in the pilots*. The participants of the study designed the observation protocol which was used in the different pilots. This paper focuses on the iterative, exploratory data analysis of 1+5 lessons of these observations. After the analysis of 1 specific lesson, we analysed 5 more lessons through the involvement of stakeholders, by introducing different types of data in the data-set.

[3] https://vara.e-koolikott.ee/

b. Observational Data Collection Instrument - Observata

A classroom observation app, Observata (https://observata.leplanner.ee) [41], was used to design and systematically observe the lessons were the digital resources were used. Apart from supporting unstructured observations, this tool enables collecting data through systematic observations based on learning interactions (learning event is the unit of analysis). While the tool enables the connection with the predefined LD (automatically imported from LePlanner [45]), it is not compulsory. The tool also allows for inferring learning activities (emerging plan/observed lesson structure) from lesson implementation and collecting field notes (unstructured observations) and photos.

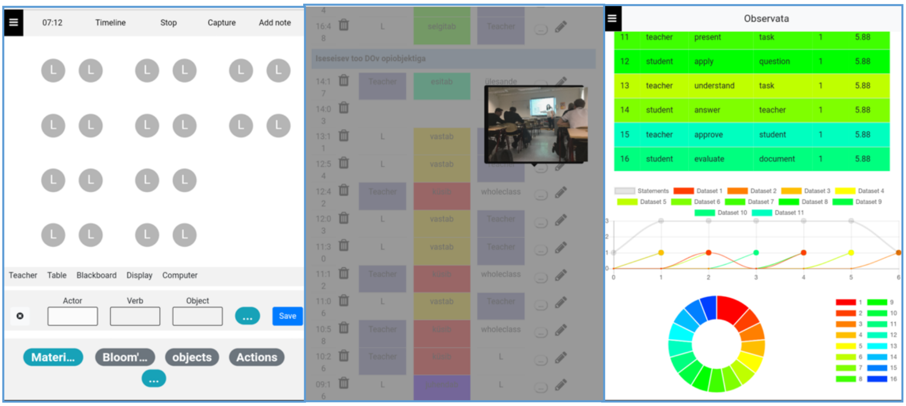

Fig. 2. Observata screens (from left to right): observation view to collect data in xAPI format, data visualised on the timeline, data visualised on the dashboards.

To aid the observation, the tool enables the user to define the foci of interest, subjects and objects up-front, speeding up the systematic observations. Observations are modelled as xAPI statements. xAPI is a specification that enables the collection of digital traces in the form of statements in a *subject, verb, object* structure that is similar to an English language sentence structure[4] (see the fig 2, left). Data can be stored and downloaded but also visualised on the timeline in an xAPI format right after the data collection (middle), and analytics with the structured observations is provided on a dashboard (right). Aside from this, Observata allows for open coding protocol while still enabling the systematic data collection.

c. Process: Involving users in the design of MMLA solutions

To better understand the added value of combining observations and digital traces to contextualise the analysis in an early stage, we followed a method to progressively involve end-users in the design of MMLA solutions [8]. While this process has only 4 steps *(a. Understanding the MMLA solution, b. Define the questions to be answered*

[4] https://experienceapi.com/overview

by MMLA solution c. Reflection on contextual constraints and affordances. d. Refinement of the scenario and customisation of the MMLA solution), we added an extra iteration of the last 2 steps. This method allowed us to iteratively analyse the data and co-design the MMLA solution, identifying indicators and visualisations that better fit the stakeholders' needs.

In the first iteration, we analysed a history lesson that took place in May 2018, lasting 40 minutes, taught by one teacher to 15 students. One observer observed the lesson. According to the data collected by the observer, the teacher followed a sequence of 6 activities, namely: 1. Introduction to the lesson. 2. Presentation of a new topic. 3. Independent work with digital learning. 4. Feedback on independent work. 5. A new presentation. 6. Quiz. Since the learning design was not formalised in advance by the teacher, this inferred structure of the lesson provided us with contextual information to understand what happened during the lesson.

Iteration 1. Step 1. Understanding the MMLA solution: Student interactions with the digital resources were collected in the form of anonymized xAPI statements. Aware of the limitations of the log analysis, the participants of the study planned observations to gather evidence about how the materials were integrated into the classroom. Also, to support the systematic collection of observations in a compatible format for MMLA analysis (xAPI statements stored in a Learning Record Store (LRS)), the project managers provided observers with Observata (section 4.1).

Table 1. Relation of needs posed by the project managers, extracted topics of interest, and allocation per co-design iteration

Participants' needs	Topics of interest addressed per iteration
Participant 1. Overall question: how are resources used? *"What happened between the subjects when one of the activities started?" (TI1)* *"Categorize situations that happened in the classroom, using them as a context for log data" (TI1, TI2)* *"Differences of implementation patterns and using the digital learning resources" (TI3)*	**Lesson level (iteration 1)** TI1. How was the interaction between the actors according to different activities? TI2. How were the interactions with digital resources according to different activities?
Participant 2. **"***Understand how teachers' integrate new resources to their pedagogical practices: do they use it traditionally to replace textbooks, more for individual work or to enhance new learning paradigms" (TI3)*	**Project level (iteration 2)** TI3. What are patterns of usage of digital learning resources?

Iteration 1. Step 2. Define the questions to be answered by MMLA solution. The main goal of the project managers was to better understand actual practices and patterns of using digital learning resources used in co-located classrooms and spot what obstacles teachers face. To this aim, several lessons were studied through systematic coding of interactions and inferring the lesson structure. In this step, the project managers posed the main questions they wanted to answer with the MMLA solution (see Table 1)

taking into account the affordances and contextual constraints (step 3) of the MMLA solution. Since these questions were of different granularity, in the first iteration we focused on lesson-level questions. Once we clarified how to study individual lessons, in the second iteration, we also addressed those questions that entailed analysing multiple lessons to extract patterns.

Iteration 1, Step 3. Reflection on contextual constraints and the MMLA affordances: The participants were informed about the limitations and affordances imposed by the observation design and the technological infrastructure. On one hand, several constraints were hindering the multimodal analysis. First, the actors were not identifiable across datasets, hindering the possibility of merging the data and following individuals across spaces. Nevertheless, independent analysis of each dataset was done and then presented together to provide a more holistic view. Second, the resources used during the session were not known. Thus, the traces stored in the LRS were manually selected based on the timeframe and the topic of the session. However, there was no way to differentiate, as these digital resources were used in another classroom at the same time. Third, additional observation statements were originally in Estonian and translated into English for the analysis, introducing potential noise in the data. Fourth, each dataset used different data values (i.e., different types of actors, verbs, and objects/artefacts). Therefore, this aspect did not allow us to run the analyses of both datasets together in a meaningful way, as mentioned in point one.

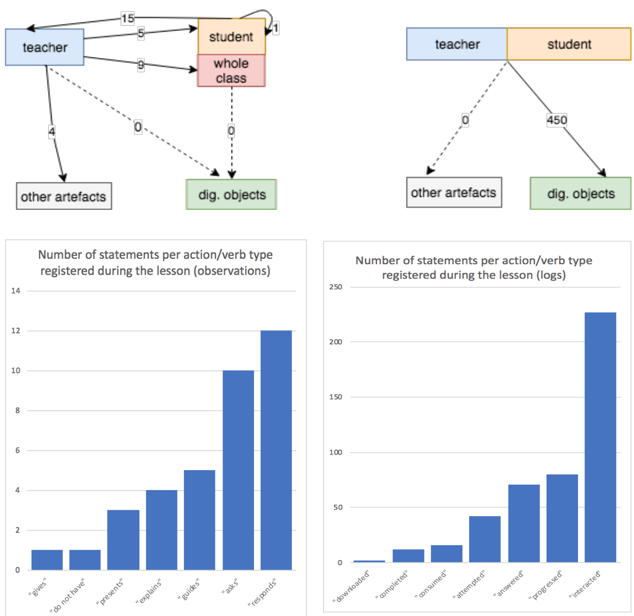

Fig. 3. Upper: Overview of the amount and type of interactions in the physical (left) and in the digital space (right) Down: the frequency of each (inter)action type or verb in observations (physical interactions) and logs (digital interactions). Note the difference in scale of each graphs

On the other hand, multimodal dataset offered multiple opportunities. First, observations and logs complement each other, offering a more holistic picture of the learning activity. Second, it is possible to analyse data within the context of emerging, observed lesson structure during the implementation of a lesson (visualised in figure 4). Finally, observation data includes different types of physical artefacts and different levels of interactions (student-teacher, teacher-student, student-student, teacher-artefact). Figure 3 provides an overview of the data collected through observations and logs, as well of the type and frequency of the interactions registered.

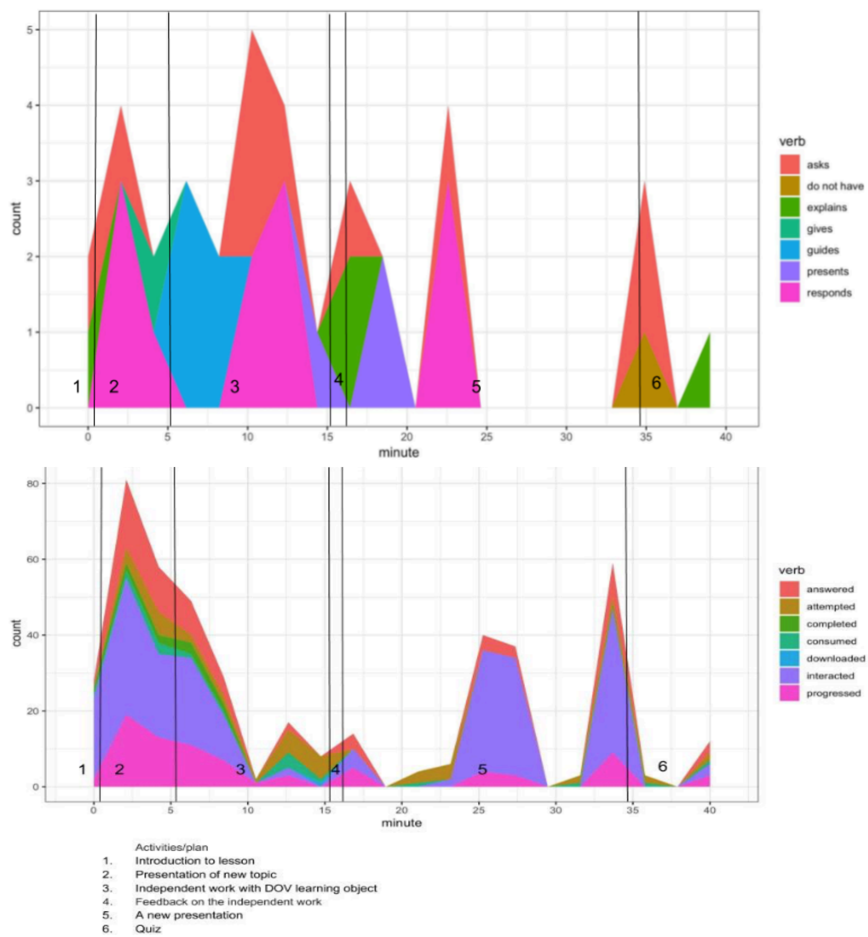

Fig. 4. Timeline representation of the interactions registered in observations (physical interactions - first) and digital traces (digital interactions - second). The vertical lines represent the limits of activities (observed lesson structure) where the interactions took place.

The data were analysed within the context of learning activities and visualised by plotting the interactions in the sequence of activities inferred by the observer. The plots were placed on top of each other. The metrics used in the analysis were chosen to meet the questions posed by the project managers: the frequency of interactions of participants contextualised within the activities and types of interactions contextualised within the activities across two datasets. Figure 4 illustrates the outcomes obtained from the analysis.

We also applied Social Network Analysis (SNA) to both datasets (eigenvector centrality measures, betweenness, page-rank, degree, in-degree and with overall network statistics). To transform the xAPI data from observations and digital interactions into graph data, actors and objects (resources in case of digital traces) were defined as nodes, and interactions (i.e., verbs) as edges, which could bidirectional (subjects interacting with objects and vice versa) or unidirectional (actors interacting with digital objects). Only one SNA graph is used to illustrate the results obtained through this kind of analysis. (see Figure 5).

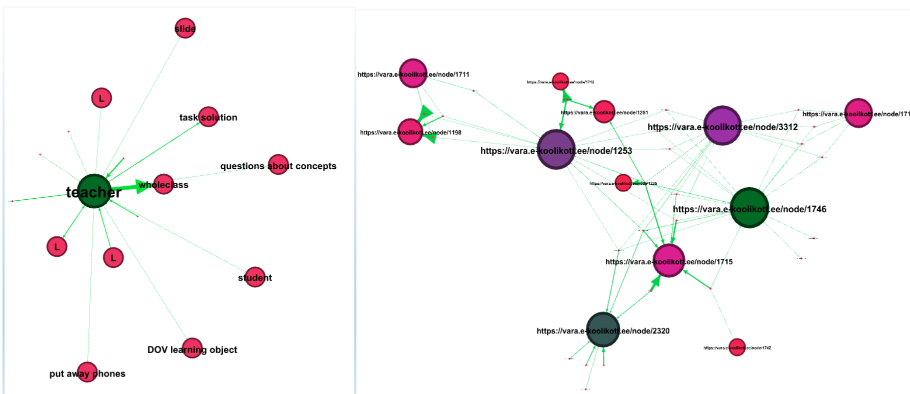

Fig. 5. SNA (on the left), SNA of logs: visualises the page-rank (colour-coded - the greener the higher is the page-rank, hence the relative importance) and Eigenvector (bigger the circle, the more influential is the node)

User feedback. The participants (i.e., the project managers) received a report including the main visualisations and brief introductions to the concepts or metrics used (for instance, for SNA terminology). Based on this report, they filled out a questionnaire[5] to collect specific feedback on indicators for further analysis, as well as general feedback on the study and datasets based on the analysed lesson. Most of the time two participants thought it was *useful* to see both datasets separately and together to understand the adoption of digital resources. They thought it was *somehow useful* or *very useful* (on a scale of *very useful, somehow useful, not useful at all)* to have data from physical and digital spaces to understand the adoption of digital resources, including not only the systematic observations and the logs but also the lesson plan inferred by the observer. SNA was not considered useful since neither actors nor resources could be identified across observations and logs, and this kind of analysis did

[5] Link to the questionnaire that includes also visualisations http://bit.ly/MMLAstudyquestionnaire

not establish the connection to the timeline or the inferred lesson plan. First iteration results and data challenges (also defined in the constraints in iteration 1. Step 3.) are reported below, which informed the analysis of the next iteration.

Table 2. List of visualisations and analysis carried out in iteration 1. For each of them, perceived added value and detected challenges are listed.

Visualisation	Analysis	Feedback and value	Challenge
Plot, time-based	Separate plots (placed on top of each other) of (inter)actions according to participants within the context of observed lesson structure	Somehow useful, useful but only observations allow for distinguishing actor roles	Student IDs missing for joint analysis, actors' roles not distinguishable in digital logs
Plot, time-based	Separate plots (placed on top of each other), plotting (inter)actions within the context of observed lesson structure	Somehow useful, useful, verbs and actions complement each other, the main value is observed Lesson Structure and xAPI	Student IDs missing for joint analysis
SNA graphs	Two graphs side by side, different analyses (eigenvector centrality measures, betweenness, page-rank, degree, in-degree and overall statistics).	Not useful or somehow useful, no value at this stage	Missing IDs, no context was given so SNA graphs are disconnected. Actor roles are not distinguishable

After the questionnaire, unstructured interviews were also scheduled. The results from this questionnaire and interview are summarized in Section 5.

Iteration 1. Step 4. Refinement of the scenario and customisation of the MMLA solution. The feedback obtained from Iteration 1 (see Table 2) informed step 4 and further analysis. While both participants acknowledged the added value of using observations to make sense of what happened in the classroom at the physical and digital level, several ideas emerged to improve the MMLA solution. Apart from the mere integration of MMLA dashboards with the observation tool, new relevant data sources that could contribute to the contextualisation were mentioned. This includes: teachers' reflections and observations (even if they are not systematic), the LD inferred by the observers, or LD provided a-posteriori. Presenting the visualisations together with explanations, in a storytelling manner, was well appreciated by the participants of the study. Based on the study, the project managers would like to explore which (novel) learning activities were designed around the usage of digital learning resources to support different learning paradigms.

Fig. 6. Examples of visualisations generated during the second iteration: on top - interactions in digital space, in the middle - interactions from physical space with field notes[6] and logs. In the bottom - the number of the observed actions per actor, the teacher is dark pink) contextualised in observed lesson structure.[7]

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[6] black boxes on the plot mainly describe additional information as noted by the observer i.e., the last comment reads: teacher announces that who left earlier will be graded after. Normally, in Observata this is visualised on the timeline, timestamped.

[7] Link to the analysis and questions http://bit.ly/MMLA5morelessons

Iteration 2. Step 3. Reflection on contextual constraints and the MMLA affordances. To answer the project level questions defined in iteration 1 (see Table 1), we extracted the main constraints and affordances of each data analysis and have chosen metrics and indicators that were meaningful for the stakeholders (Table 2). Five more lessons were analysed taking into account the lessons learnt from the previous iteration. As SNA was not regarded as useful, we omitted it this time. In some cases, together with xAPI statements from observations, logs from LRS and emerging lesson structure, we used observer field notes and teacher reflections.

User feedback: A semi-structured interview was carried out after providing participants with a report containing the analysis of the 5 lessons. The goal of the interview was threefold: to evaluate to what extent the MMLA solution helped the *answer* their project-level questions; to understand the value of combining different data sources and added value of each of the data sources, and finally, to identify further needs in terms of data collection or analysis to understand patterns of use. The interview data is analysed and reported in the results section.

As it happened in the first iteration, the participants highlighted the added value that having an LD could bring. However, in this second iteration, they also acknowledged that teachers did not always agree on documenting and sharing their LDs. Moreover, participants indicated the importance of having two types of contextual information – together with predefined LD observed lesson structure inferred from lesson enactment can be layered. It was suggested to use dashboard capabilities for the sensemaking of data. Different other data sources could help fill in missing information, for instance, videos that can be later coded and structured. This raises data privacy issues that are sometimes difficult to manage (just like in case of this particular project).

Iteration 2. Step 4. Customisation of an MMLA solution: Several ideas emerged to improve the MMLA solution. While separate datasets without predefined LD are still informative to answer the project-level question, predefined LD is necessary to have richer analysis. Actual implementation patterns extracted through observed lesson structure can only enrich the data and further contextualise its analysis. It is desirable to include different data, amongst them qualitative, that through the development of the MMLA solution could be further quantified. For instance, short videos for later annotation or post-editing of unstructured field notes. The solution will need MMLA dashboard development to enable further sense-making of data since several qualitative and quantitative data-sources are regarded as useful by the stakeholders.

d. Results and discussion

This section presents the results of the questionnaire and interview data analysis from both iterations. The qualitative feedback from the participants from both iterations are reported together was analysed following the research questions of the paper: the table 3 (see Appendix 1) summarizes the findings and brings evidence from questionnaires and semi-structured interviews in iterations 1 and 2. Based on the main findings of the research we will interpret the results following two main research questions:

RQ1: Which aspects of digital-trace based LA could benefit from the observations?

Following the method, the feedback received from the users led us to the design ideas for the next version of the MMLA solution. Additionally, the lessons learnt also helped the project managers to consider the constraints of the context and the affordances of the MMLA solutions, guiding the design of future studies.

Structured Observations: According to the participants, the main benefit of the observations for the MMLA solution was structured observation data in the form of xAPI statements which bring different dimensions for the data analysis.

Semantics: Participants noted that data from two realms introduce different semantics: while it may be useful to see same taxonomy in both datasets (xAPI statements in the logs and observations), it's not an absolute solution because these two data streams represent different semantics.

Inclusion of other qualitative data sources: According to the participants, aside from structured observation data MMLA that can easily be created by annotating learning events, Multimodal analysis can also benefit from unstructured observations (field notes, observed lesson structure). While unstructured observations present more integration challenges that structured ones, they could be of great value to interpret the quantitative results as well as to triangulate and validate the findings. For instance, timestamped field notes, photos and videos may provide further qualitative context. Also, teacher reflections may be used to partly replace missing predefined LD to understand teacher intentions. This also can be timestamped photos or videos that can be coded later. Using storytelling approaches to present quantitative and qualitative data could be a promising solution. In this case, the quantitative data analysis could help to contextualise what was happening when the qualitative evidence was gathered.

Data analysis, sensemaking and multimodal dashboards: According to the participants, the data collection, analysis and sensemaking of data can be contextualised within planned LD. Emergent, observed lesson structure can add another layer of contextual information. Codification – annotating interactions gives context to the log data. Even if observations are useful for contextualisation, they do not replace the LD. Having both, the original teacher design and the emerging one inferred from the observations would add value to the data analysis, enabling the comparison between plan and implementation, as well as detecting regulation decisions. As qualitative data was regarded useful and important, some of this data can be post-edited and structured but some qualitative data (with different semantics) also visualised on the dashboards and sensemaking of data can be aided through filtering.

*RQ2: What is the added value that **observations** offer to the user in terms of meaning, context and quality?*

Meaning and complementarity. According to the participants, observations add value through incorporating additional data on actor roles, actions (verbs) and artefacts (objects): it is not possible to make sense of the data without putting logs and structured observation datasets together. Only the combination of the two contributes to sensemaking. Data coming from the different spaces complement each other and are only useful if put together. Different semantics from across-spaces data also bring complementary information.

Context/theoretical grounding. According to the participants, the contextualisation of digital data is the main value of classroom observations. This contextualisation can happen through: unstructured observations (observed lesson structure), coded (inter)actions aggregated through structured, semi-structured xAPI statements or unstructured field notes later coded/edited and systematized. Participants stressed the importance of theory-driven coding: theoretical (learning) constructs [32] can be introduced through the pre-defined codes, aligning theory with data to enable confirmatory analysis.

Quality. According to the participants, most of the quality issues were related to the constraints posed by actual research design, that is an authentic, typical scenario. But at the same time, they relate to privacy issues, mentioned by the stakeholders. Therefore, the actual data was *puzzling, exploratory and incomplete*. While it was possible to gather multimodal data from the digital and the physical space, a joint analysis was not possible in some cases (actors could not be identified across datasets) and not meaningful in others. *Observations represent small data* – nevertheless, they bring different semantics and context in the data set, which is an important issue in LA.

Based on the feedback from the questionnaires and interviews, we have gathered insights about the value that classroom observations add to the data analysis. Regarding the value of observations, several dimensions were highlighted. First: *Context on the implicit lesson structure can come from unstructured observations,* derived from the enactment of the lesson and inferred by the observer. This reinforces the need for connection to planned LD that shall be made available through technical means. In this case, it would be advisable to further contextualise the data collection and analysis within planned LD while not excluding, but complementing it with unplanned, implicit design decisions through observer inferred patterns. Second, *theoretical constructs can be introduced through the structured codification* of observable learning events for richer data analysis. Third, the *availability of information of different kinds of artefacts from physical settings enriches the digital data*. Fourth, actor roles – *observations can provide with more detailed information on actor roles and their actions in the real world*. Fifth, at this stage, *two data-sets were presented separately to look for the value of each one, help define further requirements for the data analysis*. The aim of alignment should not be a complete integration, as these two datasets represent two different realms, but it has to be complementary, gathering complementary insights, in this case, learning context. At a technological level, depending on the analysis or sensemaking aims and methods, the alignment between semantics may or may not be needed. Nevertheless, learner level analysis can be accomplished by developing compatible coding schemes for MMLA observations that can introduce theory-based, confirmatory analysis.

First of all, according to the participants, systematic or structured observations allow for quantitative analysis of data while still offering richer context derived through non-automated means. xAPI statements from observations and can be potentially used for MMLA analysis. Results show that participants have seen the value also in qualitative observations, provided that they can be later structured and coded, or recoded to ensure reliability. Other qualitative data sources such as teacher reflections can provide increased contextual information where this context is missing: qualitative data validates and triangulates data gathered through automated means and contextualises it.

Additional findings: going back to the suggested *Context-aware MMLA Taxonomy*, based on the results of the study, balance is needed between user needs and data affordances, and needs for contextualisation for analysis and sensemaking. Depending on these needs, data can be further structured - for instance, field notes and photos can be coded later and timestamped). Different data sources can be further included to enrich the evidence, validate, triangulate findings or contextualise the data. Automated or human-mediated data brings different semantics and meaning in the datasets. Each level of the taxonomy can be used for different types of research designs [22], i.e. the use of highly structured observations based on predefined coding can contribute confirmatory research and creation of hypothesis space through *labelling* of learning constructs within MMLA as indicated by other researchers [32]. Overall, based on the feedback of the users ideal, authentic or limited scenarios of data collection and analysis, the benefit of contextualisation for data analysis and sense-making is evident. However, taking a step further towards an ideal case, we can envision that structured data gathering can contribute to three-level contextualisation of data through *predefined design, observed lesson structure*, and *structured observations*. Additionally, according to the participants, sense-making can be further supported by the introduction of multimodal dashboards with by making the data sources manipulation possible, where even qualitative information can be timestamped and visualised. Overall, our findings indicate the importance of guided data collection and analysis [25] and contextualisation of LA data [1] on different levels. At the same time, participants reported that the need for compliance with data privacy regulations is pushing the providers of educational technologies to anonymize digital traces by default. This design issue introduces an extra level of complexity since it is not possible to identify users across datasets, which is essential for MMLA purposes.

According to participants views, CO can support different layers of contextualisation (collected with the help of Observata). The figure below (Fig.7) sums up the contextualisation needs highlighted by the participants, supported by our approach and afforded by Observata, range from limited to ideal scenarios. Several levels of contextual information can be layered and obtained from: first, predefined LD, second - observed lesson structure, and the third - systematic observations MMLA and LA and CO within LD; MMLA and LA) and HMO within LD and/or inferred lesson structure, AO within structured observations In ideal scenarios all of they can be layered to augment the contextualisation efforts. An additional layer of contextualisation (Fig. 7, in blue) can happen by other qualitative data, which, while is supported by Observata, goes beyond the scope of this research and claims, can be still collected qualitatively (photos or fieldnotes) and later structured using Observata post-editing feature of learning events.

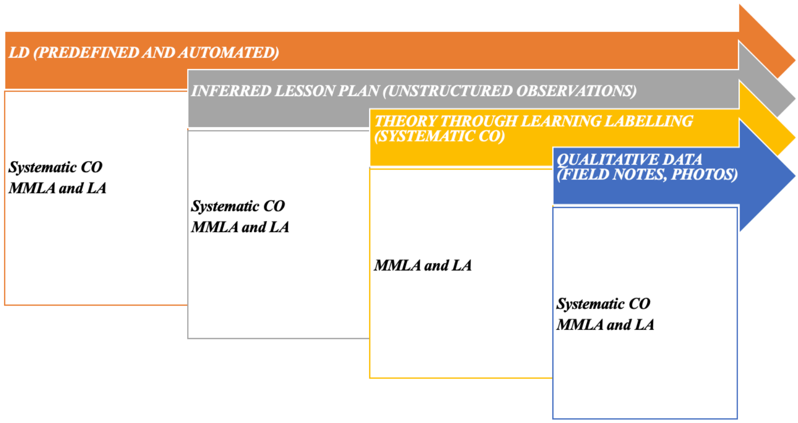

Fig.7. Layered contextualisation levels supported by and afforded by Observata

Reflecting on the methodological approach followed in the study, the co-design method [8] allowed us to take a closer look at the value of the datasets and customize the MMLA solution iteratively, that was the direct aim of the study. Through iterative, exploratory approaches we have been able to evaluate and explore challenges and opportunities of the MMLA solution. Even though involving participants across the different iterations and steps was tedious and time-consuming, it allowed us to better understand the needs of the participants, address the challenges they face while using MMLA solutions, and help them better understand the affordances that these solutions may bring into their practices. At the same time, their involvement in the data analysis in the context of the authentic scenario created new avenues for the design of the MMLA solution.

5 Conclusions and future research

In this paper, we sought to understand the feasibility and added value of contextualising the analysis of digital traces with classroom observations. To accomplish this aim, we have presented a case study from an authentic, baseline scenario using data collected from structured and unstructured observations, interaction logs, field notes and teacher reflections. According to the participants' feedback, observations contribute with contextual information for analysis and sensemaking of digital traces. Case study results show that both, systematic and unstructured classroom observations contribute to the contextualisation of the analysis of automatically-collected data (i.e., logs from the digital learning resources) which represents their main value. While the observations and observed lesson structure can be useful to contextualise both datasets, it does not make the LD less valuable for higher-level analysis [12]. To participants' beliefs, the combination of both predefined and observed designs is an ideal scenario for more thorough reflections. Also, enabling actor identification or at least differentiating roles across datasets would make the analysis more meaningful. According to the participants, distinguishing between different taxonomies (verbs) used in observations and digital data may be interesting due to different semantics digital and physical realms entail, but in some cases, it might be also useful to align them.

As already acknowledged in the *MMLA context-aware taxonomy*, authentic studies, such as the one presented in this paper, pose multiple limitations in terms of the data available and its quality. Also, it should be noted that the low number of participants involved in our case study prevents us from generalizing the results.

To bring authentic scenarios closer to the ideal case, in the future it would be recommended to include more systematically collected data. Also, for further contextualisation of the MMLA data for analysis some methodological, technological and research needs are to be addressed. To reach those goals, the observation tool used in our study — Observata, will be further developed according to the findings of the study. In addition, aspects such as data reliability and validity as well as data privacy issue should be addressed in the future both at the technological and methodological level.

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Appendix 1

Table 3: summary of findings mapped on the evidence from two iterations of co-design and data analysis. Statements included in the evidence is the summary of key messages from the evidence. Italics bring quotes from participants.

Findings	Qualitative evidence (2 respondents, 2 iterations)
It is possible to extract knowledge from two data-sets (classroom observations and digital logs)	Patterns of usage by using two-datasets: *"Yes, more or less I am able to do it."* *"Yes, Patterns seen on didactical use and some unexpected patterns can be definitely seen and guessed from this data"*
The complementarity of the physical and digital traces was considered an added value.	Extracting knowledge only based on one data-source: *"No, certainly not."* *"No, definitely no"* *"There is definitely an added value here."* Two data sets complementing each other: *"Observations help me also to see what activities were happening at the same time in the classroom".* *"Only observations plot made me think about what happened during the minutes 14-19, but logs data made me understand that it was independent work probably with DÕV… probably it was teacher-centred activities"*
Both, exploratory or confirmatory analysis is possible.	It can be used for exploratory and confirmatory purposes: *"Only when I see both together. With only one, there is no question even raised." "Visual cues that raise more questions, questioning each data set". "If the questions were asked before then we would have theory-based coding and it would have been more confirmatory".*
Observations enable contextualisation while connection to theory is equally important **1. Emergent/observed lesson structure fills the gaps for missing predefined LD information for contextualisation of data. Makes differences between implicit and explicit LD evident by providing two layers of contextual information – Predefined LD and observed lesson structure.** **2. Coded (inter)actions themselves explain digital interactions, at the same time, bring another layer of context through theoretical concepts**	Contextualisation and analysis based on (observer-inferred learning activities): It is useful to *"see interactions per actor in different phases of a lesson (learning activities that have been coded by an observer)".* *"For me, it is not important if the homework's were checked, but rather how it was checked, did it support students' SRL, did they take some responsibility in the process"* Predefined LD and observed lesson structure*:* it "*give two layers of contextual information - planned design vs actual, enacted design not only in terms of planned vs real duration but in terms of implicit vs explicit design, emerging design decisions etc. This should be fed back to the lesson scenario digital representation to understand the patterns of actual enactment". "LD creates the loop to actual activities and*

	implementation, and learner actions answer to why dimension" Coded actions (observations): "*observed and coded (inter)actions represent valuable information explaining digital interactions: physical interaction data gives context to the digital interactions, without this context 450 digital interactions data have no value"*. According to the participants, *"observations in physical space enhance the context of digital interactions"*. Connection to theory*:* *"Observations allow for analysis of social negotiation of meaning in the classroom and intentionality behind pedagogical decisions of the teacher while online (automatically harvested) traces only a fact of interaction."* *"While it is important to link activities with lesson goals/tasks, their duration and curriculum objectives, sometimes it is useful to link them with some theoretical constructs (e.g., communication acts or taxonomy of objectives/adoption/acceptance), aligning learning theories with data"*.
Unstructured, qualitative data such as field notes or teacher reflections enrich the data-set further with context. **Structured data is preferred for the analysis: all the observations are to be systematized (structured), edited and merged.**	Qualitative, unstructured data: *"It [unstructured observations, field notes] enriches the context remarkably, I understand better some levels of interactions."* *"Field notes in our case contain spatial information (potentially can contain notes on discipline), photos also help, they have a timestamp, so they can help you make sense in case of missing information"*. Structured observations are preferable: *"Unstructured observations can be used for emerging patterns, to post-edit it and code them to make them structured."* *"Data can come as unstructured and then coded and structured in xAPI statements."*
There is a need for further validation and triangulation	Other data sources such as teacher reflections or field notes (unstructured observations) add more to the context and validate and triangulate the data: *"It gives the final touch what happened in the classroom and why"*. *"Two datasets together - logs and observations It helps you to raise questions but does not validate. Validated by reflections, or field notes. Triangulation of data"*.

There is a further need for data collection and analysis. For instance: easy to capture data such as short videos (in case of privacy issues can be replaced by audio), classroom media usage automated data, reliable and complete online interaction data, predefined LD, data visualisation techniques- dashboards	Need for more data sources: "*Easily captured data, for instance, noise to give more contextual information"* *"Video that may be related to legal issues, can be solved by recording only audio. Automatically generated events on interactions in the classroom media use. Completeness of data from online settings is necessary"* *"Photos and videos to be later coded and integrated"* Sensemaking and analysis level: *"LD and data in a way I could understand if it was more student-centred or teacher-led"* *"dashboards with different data streams customizable by the user for sensemaking."*
Two datasets bring different semantics from different realms and dimensions	Data integration and semantics*:* *"it was very interesting to see this figure where xAPI verbs and Observata "taxonomy" were demonstrated together - seeing them based on one lesson would be extremely interesting"*. *"It is obvious that two realms bring on different semantics, in some cases, it may be useful to see the same taxonomy in both datasets"* in some cases, *"it would be confusing"*.
Quality issues on data collection and analysis level: some information is missing	Data can be puzzling and incomplete: *"The amount of coinciding physical vs digital interactions is puzzling"*. *"I would expect the digital interactions increase when physical interactions decrease (teacher stops talking), but according to this graph, this is not always the case"*. *"The records of actions in physical space are clearly incomplete due to time constraints to annotate the within-group and between-group activities"*. Learner identification is important in enabling learner level analysis: **"***Usefulness increases significantly when learners are identified across both physical and digital spaces"*. **"***the quantity and variety of traces are significantly smaller in physical space"*.