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LEARNING INTERACTIONS ACROSS SPACES: A FRAMEWORK FOR CONTEXTUALISED MULTI-MODAL OBSERVATIONS

Tallinn 2020

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LEARNING INTERACTIONS ACROSS SPACES: A FRAMEWORK FOR CONTEXTUALISED MULTIMODAL OBSERVATIONS

School of Digital Technologies, Tallinn University, Tallinn, Estonia

The dissertation was accepted for the defence of the degree of *Doctor Philosophiae* in Information Society Technologies by the Doctoral Studies Council of Natural Sciences of Tallinn University on March 18th, 2020.

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LIST OF PUBLICATIONS

The dissertation is based on these seven papers, which are referred to in the analytical overview by Roman numerals:

I. **Eradze, M.,** Pata, K., Laanpere, Mart (2015). Analyzing Learning Flows in Digital Learning Ecosystems. *In: Yueh-Min Huang, Frederick Li, Qun Jin (Ed.). Advances in Web-Based Learning – ICWL 2013 Workshops (63−72).* Berlin-Heidelberg: Springer Heidelberg. (Lecture Notes in Computer Science; 8390).

II. **Eradze, M.**, Väljataga, T. Laanpere, M. (2014). Observing the use of e-textbooks in the classroom: towards “Offline” Learning Analytics. New Horizons in Web Based Learning: ICWL2014, Tallinn, 14-17th of August. Toim. YiIi Cao, Jeff K.T. Tang, Howard Leung, Mart Laanpere. Switzerland: Springer, 254−263. (Lecture Notes in Computer Science; 8699).

III. **Eradze, M.,** Rodríguez-Triana M.J., Laanpere M. (2017). How to Aggregate Lesson Observation Data into Learning Analytics Datasets? *MMLA and Cross-LAK Workshops 2017, 1828: Joint Proceedings of the Sixth Multimodal Learning Analytics (MMLA) Workshop and the Second Cross-LAK Workshop co-located with 7th International Learning Analytics and Knowledge Conference*, Vancouver, Canada, March 14, 2017. CEUR Workshop Proceedings, 74–81.

IV. **Eradze, M.**, Rodríguez-Triana, M. J., & Laanpere, M. (2017). Semantically annotated lesson observation data in learning analytics datasets: a reference model. *Interaction Design and Architecture (s) Journal-IxD&A*, *33*, 75–91.

V. **Eradze, M.,** & Laanpere, M. (2017). Lesson Observation Data in Learning Analytics Datasets: Observata. *In European Conference on Technology Enhanced Learning* (pp. 504–508). Springer, Cham.

VI. **Eradze, M.,** Rodríguez-Triana, M. J., & Laanpere, M. (2019). A Conversation between Learning Design and Classroom Observations: A Systematic Literature Review. *Education Sciences*, 9(2), 91.

VII. **Eradze, M.,** Rodríguez-Triana, M. J., Milikic, N., Laanpere, M., Tammets, K. (2020). Contextualising Learning Analytics with Classroom Observations: A Case Study *(accepted) to Interaction Design and Architecture(s) Journal).*

Other relevant publications in the area:

VIII. **Eradze, M.,** Rodríguez Triana, M.J., Laanpere, M. (2020). Context-aware Multimodal Learning Analytics Taxonomy. *CrossMMLA2020, Companion Proceedings of Learning Analytics and Knowledge Conference (LAK),* CEUR Workshop Proceedings*, Frankfurt, Germany.*

IX. Rodríguez-Medina, J., Rodríguez-Triana, M. J., **Eradze, M.**, & García-Sastre, S. (2018). Observational Scaffolding for Learning Analytics: A Methodological Proposal. *In European Conference on Technology Enhanced Learning* (pp. 617–621). Springer, Cham.

X. **Eradze M.,** Laanpere M. (2014) Interrelation between Pedagogical Design and Learning Interaction Patterns in different Virtual Learning Environments. *In: Zaphiris P., Ioannou A. (eds) Learning and Collaboration Technologies. Technology-Rich Environments for Learning and Collaboration. LCT 2014.* Lecture Notes in Computer Science, vol 8524. Springer, Cham.

Author's contribution

I. The author was responsible for the research strategy, has analysed the literature and written the article. The co-authors have contributed to the review and writing.

II. The author was responsible for the literature review, development of the research instrument, data collection, data analysis and has written the article. The co-authors have contributed to research design and writing.

III. The author was responsible for the main theoretical concepts developed in the article, the research strategy and has written the article. The co-authors have contributed to the research strategy, reviewed and contributed to the article writing.

IV. The author was responsible for research strategy, data collection instrument, data analysis and interpretation and has written the article. The co-authors have contributed to data collection, reviewed and contributed to the article.

V. The author was responsible for writing the article, the co-author has reviewed and contributed to article.

VI. The author was responsible for the research strategy, data collection, data analysis, interpretation of results and has written the article. The co-authors have contributed to data interpretation, reviewed and contributed to the article.

VII. The author was responsible for the research strategy, data collection instrument, data analysis, interpretation of results and has written the article. The co-authors have contributed to research strategy, data collection, have reviewed and contributed to the article writing.

ABBREVIATIONS

TEL – technology-enhanced learning

LA – learning analytics

LD – learning design

MMLA – multimodal learning analytics

CO – classroom observations

HMO – human-mediated observations

AO – automated observations

HCI – human computer interaction

RBD – research-based design

DBR – design-based research

LRS – learning record store

xAPI – experience api

ABSTRACT

Teaching and learning processes take place in blended learning settings. To create a holistic picture of educational context and analyse these processes for different purposes, different data sources and collection methods come into play. Learning interaction analysis has been an important part of the Technology-enhanced Learning (TEL) research; the data collection and analysis can happen through traditional or modern data-collection methods, gathering insights from physical and digital spaces. Technological advancements brought the need for analysis of digital interactions (Learning Analytics, LA), covering only one part of the educational process. To respond to the problem of so-called street-light effect and one-dimensional data sources, in recent years Multimodal Learning Analytics (MMLA) field emerged, combining different data-sources from traditional or modern data collection techniques coming from across space interactions, also from physical settings: sensors, EEG devices etc. At the same time, to guide the data collection process or to analyse digital traces and data collected through automated means, contextual information such as learning design (LD) with teacher intentions, actors, roles, media use and other information are needed.

Traditional data collection methods, especially qualitative methods, can respond to this need as they often contain highly contextual information. Traditional classroom observational methods are relevant and useful sources to include in the analysis for different purposes: to gain evidence from physical space, triangulate the findings, contextualise data analysis and support sensemaking of digital traces. On the other hand, human-mediated classroom observation methods also benefit from automated observations (MMLA data) and can enrich the data, speed up the observation process or gather evidence on indicators unobservable to the human eye. Aligning traditional (human-labelled) and modern (automated) classroom observations, therefore, is beneficial for educational research and practice. Previous research indicates that the fields of LD and LA have a synergetic relationship, where LD contextualises data analysis and LA informs LD. At the same time, connecting these three factors: human-mediated, automated observations and contextualisation of data analysis with LD is not a trivial task and special attention needs to be given to the specificities, meaning, affordances, constraints and quality of the data sources. To provide with a holistic picture on teaching and learning processes this research has connected two research paradigms and focused on the development of conceptual and technological tools to create links between different sources of data and the contextualisation through the development of *The Framework for Contextualised Multimodal Observations*. The Framework was developed through research-based design methodology and is implemented through a classroom observation app *Observata* — Classroom Observation tool that produces LA compliant data with specific context and LD (or without). The *Framework* consists of accompanying three contributions: *the model and the protocol for MMLA observational process,* the *Model for Contextualised MMLA Observations*, *Context-aware MMLA Taxonomy*.

L'amor che move il sole e altre stelle.

Dante

I devote this work:

To my beautiful and courageous mother – Tina. I have inherited inquisitive mind from her, and the childhood memories filled with sounds of piano. She has nurtured the thirst for knowledge in me; as a child, any question I had, my mother was the first reference point to start the exploration. She has been the one supporting all my decisions related to learning and adventures, has followed and supported me in every step.

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Κι αν πτωχική την βρεις, η Ιθάκη δεν σε γέλασε.
Έτσι σοφός που έγινες, με τόση πείρα,
ήδη θα το κατάλαβες η Ιθάκες τι σημαίνουν

(And if you find her poor, Ithaka won't have fooled you.
Wise as you will have become, so full of experience,
you will have understood by then what these Ithakas mean)

K. Kavafis

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INTRODUCTION

Educational processes increasingly take place across spaces, in blended learning settings, where technological and physical classroom contexts merge. To create a holistic picture of teaching and learning processes the educational processes in hybrid spaces, different data sources and collection methods are needed for analysis. The data collection and analysis can happen through traditional or modern data-collection methods (surveys, classroom observations or automated means), gathering insights from physical and digital spaces with different sources of data, such as observation data or logs.

Interaction analysis is an important part of the research and inquiry into teaching and learning practice and has been studied from different perspectives and paradigms (Söller, Martínez, Jermann, & Muehlenbrock, 2005). With the widespread adoption of digital learning platforms, the Learning Analytics (LA) community emerged, mainly focusing on the analysis of digital interactions (Ochoa & Worsley, 2016). However, depending on the learning activity, meaningful interactions may also not be tracked by digital learning platforms (Ochoa & Worsley, 2016). Thus, narrowing down the interaction analysis to the data available in the digital platforms could cause a street-light effect (Freedman, 2010). To respond to this limitation, a new wave of Multimodal Learning Analytics (MMLA) solutions has emerged, promoting the data collection of analysis from different data source and spaces (Blikstein & Worsley, 2016). Typically, MMLA datasets include not only log data but also data generated by sensors located in mobile and wearable devices (Ochoa & Worsley, 2016). In order to make sense of the MMLA data, input from humans is often used. For example, contextual information such as the learning design can guide the data collection and interpretation (Lockyer & Dawson, 2011) (Rodríguez-Triana, Martínez-Monés, Asensio-Pérez, & Dimitriadis, 2013). In addition, human-mediated labelling is often used to relate raw data to more abstract constructs (Worsley et al., 2016)(Di Mitri, Schneider, Klemke, Specht, & Drachsler, 2019).

Traditional data collection methods in the physical space can be represented by (human) observations. Through observational methods, quantitative and qualitative data can be systematically collected and analysed (Cohen, Manion, & Morrison, 2018). Similarly, to those focused on the digital space, observations may provide a partial view about the interactions taking place in technology-enhanced learning contexts. Besides, despite the richness of observational data, several constraints that prevent researchers and practitioners from applying them (e.g., time-consuming data collection and analysis, intrusive approach, difficulties registering fine-grain events or multiple events at the same time, etc).

Since observations could aid the MMLA contextual and methodological needs, and MMLA could alleviate the complexity and workload of human-driven observations, this PhD thesis proposes combining both approaches for a bidirectional benefit. More concretely, this work explores the synergies between these two approaches in classroom settings. Also, to reinforce the contextualisation, whenever available, this thesis proposes to use the learning design since it reflects the pedagogical grounding and the teacher intentions that lead the learning activity. Thus, in this work I hypothesize that traditional observations are a relevant and useful data source to include in the analysis, to gain more evidence from physical space, triangulate the findings, contextualise data analysis and make sense of digital traces. On the other hand, human-mediated classroom observation methods also benefit from automated observations (MMLA data) can enrich the data, speed up the observation process by automatization or gather evidence on indicators unobservable to the human eye. Aligning traditional (human-labelled) and modern (automated) classroom observations, therefore, are beneficial for educational research and practice. Last but not least, as already indicated by previous research, the fields of LD and LA have a synergetic relationship, where LD contextualises data analysis and LA informs LD.

To provide a contextualised and holistic view of the teaching and learning activities taking place in TEL classrooms by connecting two research paradigms, this PhD thesis proposes conceptual and technological tools to support the alignment of learning design, classroom observations and (multimodal) learning analytics. Through a research-based design methodology (Leinonen, Toikkanen, & Silfvast, 2008) this research has resulted in two main contributions: The Framework that integrates these three areas, and a tool that implements the framework: Observata[1]. Both the Framework and tool have been iteratively designed and tested involving final users in the process. Aside from this, other 3 contributions have been delivered: *The model and the protocol for MMLA observational process, The Model for Contextualised MMLA Observations*, and *Context-aware MMLA Taxonomy*. As part of this PhD, 1 systematic literature review, 1 participatory design session and 2 case studies (one co-design) took place, involving overall more than 10 researchers and practitioners.

The present thesis is an article-based work coherently reporting and connecting six published and one yet to be published (accepted) paper. The thesis is organized in the following chapters: after introductory parts, the first chapter describes the research at a glance, with context, research problems, main research question, objectives and contributions; The second chapter provides with the theoretical foundation for the thesis, the third one defines the research problem and questions; The fourth chapter gives the account on overarching research methodology as well as the detailed overview of each article's research design, research problems, questions and data collection and analysis methods; The fifth chapter provides results and findings from the seven research articles as a result of these studies; The sixth chapter draws the conclusions and indicates to future research and development directions; The final part of the thesis contains all the articles discussed in this thesis.

[1] https://observata.leplanner.ee/en/

1. RESEARCH AT A GLANCE: OBJECTIVES AND CONTRIBUTIONS

Figure 1 provides an overview of the whole research including the context and problems detected in the research communities and the main gaps this thesis is addressing, presents the main research question and objectives driving this 7-year work, as well as the contributions that emerged and the different evaluations they went through.

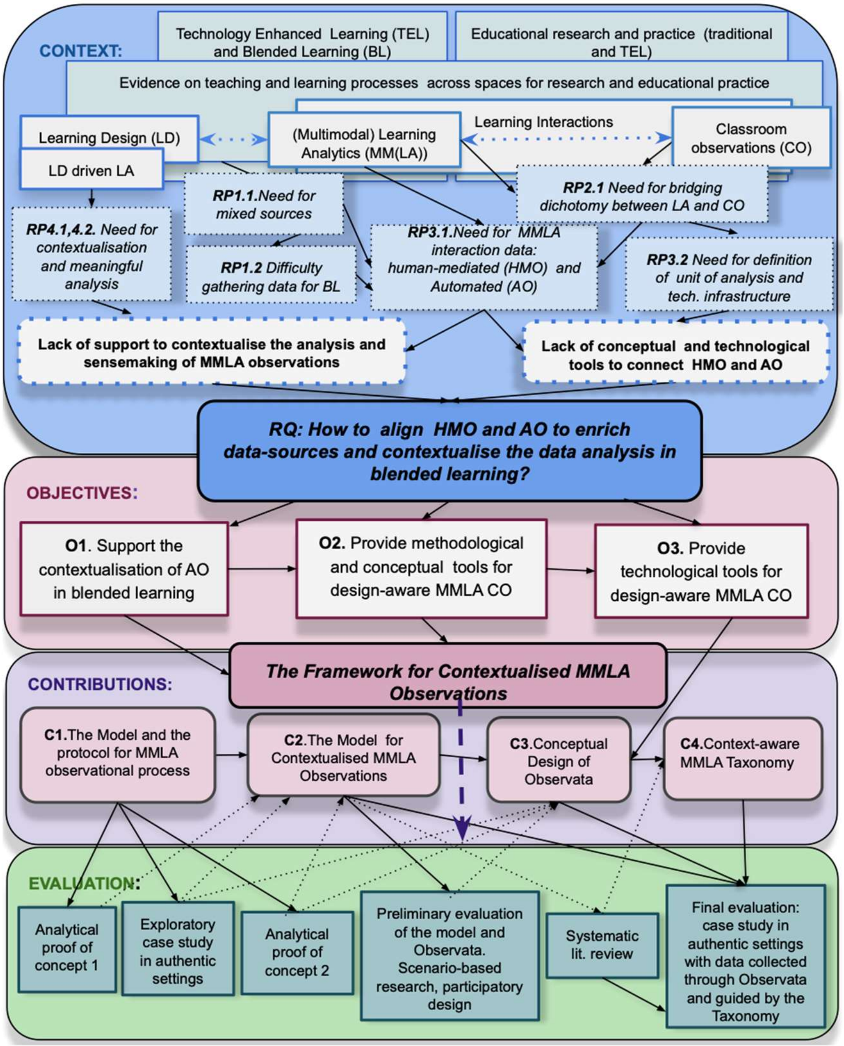


Figure 1 Context, research problem and research question, objectives, contributions and evaluation/validation schema

The overall objective of this research is the *Alignment of Human-Mediated (HMO) and Automated Classroom Observations (AO) and Learning Design (LD) to enrich the data-sources and contextualise the data analysis in blended learning.* This main objective is then broken down two 3 main objectives followed in the present thesis:

- Support the contextualisation of AO in blended learning
- Provide methodological and conceptual tools for design-aware MMLA co through Research-based development of the Framework for Contextualised Multimodal Observations
- Provide technological tools through research-based development of the design of the classroom observation tool (Observata)

To achieve the outlined objectives, I took the following steps taken in each article:

- Identification of main methodological considerations for context-aware and theory-driven data collection and analysis for across spaces data, the definition of the unit of analysis and identification of feasible solutions for data collection in physical spaces (CO) (**I, II**)
- Identification of steps, characteristics of CO data collection and development of a mental prototype of the app and first version of the model (**III**)
- Development and validation of the framework for across spaces data collection, and paper prototype for data collection instrument (**IV**) (**V**)
- Conceptualization and alignment of Multimodal Observations with LD, evaluation of the framework applicability through data collected with *Observata* in authentic settings (**VI**) (**VII**)

2. BACKGROUND AND THEORETICAL CONSIDERATIONS

The context of the research is inherently interdisciplinary from field perspective - Technology-enhanced Learning (TEL) (Spector, 2012); Thus, PhD thesis combines research lines that are more traditional from educational science perspective (i.e., classroom observation and learning design) and modern, in current TEL contexts of data-enabled automatic data collection and analysis (i.e., Learning Analytics). Moreover, to design the contributions presented in this thesis, Human-Computer Interaction (HCI) methods were followed, therefore, this PhD thesis is a multidisciplinary effort. In the following chapters, I will overview the theoretical context and background with related studies to situate the thesis within the field and pinpoint to the gap this research is targeting.

2.1. TECHNOLOGY-ENHANCED LEARNING, BLENDED LEARNING - TEACHING AND LEARNING ACROSS SPACES

TEL is a field of research and practice on the cross-section of education and computer science. While there is no single agreed definition of the field (Kirkwood & Price, 2014), one definition states that *"Technology-enhanced learning (TEL) can be broadly defined as contexts that incorporate ICT technologies in support of learning"* (Kyza, 2017). We can say that TEL has been born into behaviouristic paradigm (Skinner, 1968) specific theories on how to use technology to help teaching and learning practices, started emerging later (Duval, Sharples, & Sutherland, 2017). Over the last decade, TEL has progressively moved towards more constructivist paradigms (Laurillard, 2013). While the emphasis is often on the technological infrastructure and tools (Kirkwood & Price, 2014), the driver is mostly education and learning and *"enhancement of learning"* (Spector, Merrill, Elen, & Bishop, 2014). At the same time, TEL as a field, not only needs the development of new theories but also its own methods of teaching and learning, and evidence on their effectiveness. Balachef et al (Balachef et al., 2009) list five areas on which the field of TEL is based: *the design, the computational, the cognitive, the social and cultural, and the epistemological areas.*

TEL as a field includes and can also refer to technology-enhanced classrooms ("Technology enhanced learning," 2019) as learning in the authentic classrooms happen mostly and increasingly across spaces, the boundaries and dichotomy between these spaces are disappearing as tools and resources may be mixed. These tools and resources represent digital and physical artefacts and objects. Hybrid nature of educational contexts brings its challenges and opportunities in all five areas listed above and influence overall TEL field.

Blended learning is said to be a leading paradigmatic shift in education and most of the educational activities increasingly include some form of blended approach

(Oliver & Trigwell, 2005) (Consortium, 2012)(Halverson, Spring, Huyett, Henrie, & Graham, 2017). From a functional point of view, it is defined as *"the thoughtful integration of classroom face-to-face learning experiences with online learning experiences*"(Garrison & Kanuka, 2004). While there is no one single definition of blended learning, some authors (Whitelock & Jelfs, 2003)(Graham, 2006), most widely used definition is the *"Face-to-face and computer-mediated interaction"* or *"integrated combination of traditional learning with web-based online approaches"* which has been confirmed by a literature review (Rodríguez-Triana et al., 2017). We can say that most of the time the accent falls on the hybrid or blended nature of the learning space (Pérez-Sanagustín, 2011). While the terms hybrid and blended learning are used interchangeably, they are not the same; hybridity can be identified as the *"interweaving of formal and informal social structures in an activity system and the combination of digital and physical tools mediating an individual's interaction with the world and society"*(Cook, Mor, & Santos, 2019). This is in contrast with *seamless* or *ubiquitous* learning, where mobile technologies maintain cross-contextual learning, enabling continuous learning experiences across different settings, formal, non-formal and informal (Berge & Muilenburg, 2013). Summing up, in this thesis I use the term *Blended Learning*, to accentuate the learning processes across spaces, which is the main focus of this research.

At the same time, the need for understanding teaching and learning processes that involve digital tools to enhance educational experience is an important aspect from design or technology perspective; some authors highlight the affordances of TEL creates affordances for a range of opportunities to transform the learning process (Goodyear & Retalis, 2010), such as teacher professional development (Hennessy, 2014), teacher inquiry (Mor, Ferguson, & Wasson, 2015), or classroom orchestration (Lockyer & Dawson, 2011) (Muñoz-Cristóbal et al., 2018) (Dillenbourg & Jermann, 2010). On the other hand, some authors claim that effects of this transformation and evidence for such transformation and effectiveness is still scarce (Kirkwood & Price, 2014)(De Bruyckere, Kirschner, & Hulshof, 2016), which again, requires data collection. Thus, there is an increasing need in the community for evidence-base from the educational context that contributes to assessing the role and effectiveness of TEL interventions.

2.2. EDUCATIONAL RESEARCH AND PRACTICE: TECHNOLOGY ENHANCED LEARNING PERSPECTIVE

Educational practice increasingly seeks evidence-based approaches (Knight & Buckingham Shum, 2017) and evaluation of educational efforts and technologies using applied research (Spector, 2015). Evidence usually comes from data that can be qualitative or quantitative, or most often mixed (Rao & Woolcock, 2003) and uses traditional educational research methods to collect such data (Cohen et al., 2018).

Many related fields that aim at improving educational practice, learning environments and learning outcomes rely on the data, so research and practice are increasingly intertwined, especially in TEL settings (Hennessy, 2014): the field of learning design (Goodyear & Retalis, 2010) and its synergetic relationship with data-driven approaches i.e. Learning Analytics (LA) (Lockyer & Dawson, 2011); learning sciences (Kyza, 2017); the emerging field of *precision education* that seeks to guide educational practice with evidence-based approaches relying on data from different sources to tailor instruction to learner needs i.e. personalization (Hart, 2016). Also, the development of tools and resources for TEL need evidence for the evaluation of their effectiveness (Spector, 2015).

Specifically, the TEL field increasingly relies on data-driven approaches using data from learning traces from interactions with digital artefacts, peers, and teachers, for different purposes. TEL, as a field of research, also has its own agenda for research and practice, its methods of data collection and analysis (afforded by hybrid learning spaces), that build on and inform all the above mentioned five areas of TEL (Balachef et al., 2009). However, some authors indicate to the limited range of research methods and approaches deployed in TEL (including data gathering and analysis)(Kirkwood & Price, 2014) and point out to the need for approaches suitable for blended learning gathering evidence from spaces where teaching and learning practices take place. This often requires mixed methods approaches to be deployed (Mor et al., 2015)(Cohen et al., 2018)(Daniel, 2019). The mix of spaces may also bring the mix of research paradigms that divide the learning space between "why" (contextual and qualitative) and "what" (quantitative) dimensions further (Daniel, 2019).

The field of Learning Analytics (LA) (overviewed more extensively in chapter 1.3.1) was born with advances in technology development and use in education and is mainly log data-driven. Learning analytics analyses student data and *typically employs large datasets to provide real-time or retrospective insights about the effect and effectiveness of various elements and features of learning environments* (Mor et al., 2015). Educational research and the field of analytics are often viewed as different paradigms of research; some authors present analytics approaches as the *fourth paradigm* of research, after *quantitative*, *qualitative* and *mixed methods* (Hey, Tansley, & Tolle, 2009) (Daniel, 2019). Some authors still maintain the traditional, *three paradigm view* on educational research based on a dichotomy of *positivism* and *post-positivism* philosophies, while still considering digital contexts with its challenges and opportunities in meaning-making, and affordances that are given by this new space in research (Cohen et al., 2018). However, this discourse is mostly developed around social network/media and its ethnographic context.

In parallel, Daniel (Daniel, 2019) lists several challenges towards bridging traditional and modern paradigms of research, where several issues are relevant for my research: *ontological issues* – such as context of data collection which most of the times is missing from automatically-collected data; *epistemological* that are connected to challenges of emerging research methodology, with automatically-collected data requiring a continuous negotiation of meaning*; methods and data analysis* – different research paradigms answer to "what" against "why" questions*;* Although learning analytics research and application does not always imply the use of large amounts of data, challenges and affordances of connecting automatically generated interaction data with traditional educational research methods apply also to LA research and practice.

2.3. LEARNING INTERACTIONS ACROSS SPACES - TOWARDS BUILDING BRIDGES

Researchers, designers or practitioners that study technology-enhanced learning often rely on interaction data to enhance learning (Suthers, Dwyer, Medina, & Vatrapu, 2010). Collecting data on learning interactions in technology-enhanced classrooms or observing technology-enhanced learning in authentic, co-located settings is not a trivial task (Howard et al., 2018). Interaction can be distributed across actors, spaces, learning resources, tools and time and can be synchronous, quasi-synchronous, and asynchronous, even within one data set (Suthers et al., 2010). While computer-mediation provide more opportunities for tracking digital interactions, physical world interactions present additional challenges for analytics (Siemens & Long, 2011).

This blended nature of educational processes can entail using different data collection methods, research methods and even research paradigms to understand the user interactions (Anderson, 2003; Dawson, 2010; Soller, Martınez, Jermann, & Muehlenbrock, 2005; Suthers & Road, 2015). On one hand, educational data from the digital realms is often an automatic aggregation of learning interactions with tools, artefacts and users in digital environments that can be meaningful or not. On the other hand, in physical spaces, data about interactions among users or with resources have been traditionally collected by observers, even though sensor data and automated tagging solutions have emerged in the last few years. This section introduces the main concepts related to learning interactions, defines the unit of analysis, and presents different data collection methods.

2.3.1. Learning Interactions in TEL: towards operationalisation

Apart from the general TEL interest in interactions, *interactions* have been a topic of study in blended learning settings (Drysdale, Graham, Spring, & Halverson, 2013) and a subject of analysis in co-located classrooms (Govaerts et al., 2018; Martinez-Maldonado, Kay, Buckingham Shum, & Yacef, 2017; Miyazoe, Anderson, & Ca, 2010).

While there is no single definition of interaction and/or interactivity (Kahveci, 2007) most of its definitions broadly describe emerging processes that unfold through (inter)actions between actors and objects/artefacts/resources. In the effort of providing an operationalisation of interactions valid for different instructional contexts, Wagner defines the concept of *"instructional interactions"* as follows "*interactions are reciprocal events that require at least two objects and two actions. Interactions occur when these objects and events mutually influence one another. An instructional interaction is an event that takes place between a learner and the learner's environment.* (Wagner, 1994).

Interactions have a specific function and value in education practice and research, both in face-to-face or TEL settings (Muirhead & Juwah, 2004). From a functional point of view, Holmberg emphasizes on the student-teacher interaction (usually text-based) and the teacher guiding the student through the learning process with the help of "guided didactic discussion" (Holmberg, 1995). Actors in (learning) interactions can be human and inanimate (Anderson, 2003): Moore's theory of Three Types of Interaction (Moore, 1989) provides a systematic typology of *learner-content, learner-instructor, and learner-learner* in online settings. The interaction typology was later expanded by Anderson to 6 dyads of interaction - *learner-content, learner-teacher* and *learner-learner* to include *content-teacher*, *content-content* and *teacher-teacher* interactions(Anderson, 2011). Overall, distinguishing between three types of interactions narrow the discussion down to *Learning events* (Moore in (Wagner, 1994).

As for analytical frameworks and definitions, several models consider interactions in hierarchical lenses: the Community of Inquiry (CoI) Model assumes that learning occurs within the Community through the interaction of three core elements: *cognitive presence, social presence* and *teacher presence,* going beyond social exchanges (Garrison & Cleveland-Innes, 2005). Swan (Swan, 2001) considers Three Types of Interactions and CoI interconnected (teaching presence - teacher-learner; cognitive presence – learner-content; social presence – learner-learner interactions). Suthers et al (Suthers & Rosen, 2011) with *the Uptake Framework (table 1)* directed at distributed learning*,* based on Latour's Actor Network Theory, conceptualize and represent the distributed interactions. The authors offer analytical framework suggesting that unit of interaction is relational by its nature, so the focus should be not on isolated acts, but rather relationships between acts; the framework assumes that uncovering or characterizing the organization of interaction in sequential records of *events* should be the analytic concern.

Table 1 Uptake Framework Analytic Hierarchy from (Suthers & Rosen, 2011)

Models	*Representations*
Process Trace	Log files, audio and video recordings, etc.
Domain	Entities and their relationships (types and instances of both)
Event	Sets of events (described in terms of actors, objects, time, etc.)
Contextualized Action	Contingency graphs indicating empirical relationships (contingencies) between events
Interaction	Uptake graphs (each arc corresponds to bundles of contingencies that evidence uptake)
Mediation	Associograms: two-mode directed graphs relating actors to objects
Relationship	Subgraphs of the mediation model consisting of all paths between two actors
Tie	Sociograms representing ties between actors

Summing up, I adopt the operational definition suggested by Wagner (1994). As for analytic definitions of learning interactions that are mainly *relational* (Suthers & Rosen, 2011) (Garrison & Cleveland-Innes, 2005), – I view the analytic unit of interaction as *dyadic* operationalised through different types of interactions between *actors* and/or *object*s and connected by *action (verb)* (Moore, 1989).

2.3.2. Unit of analysis for learning interactions

One of the issues that emerge when making decisions on the research design, is the *unit of analysis.* When choosing what to analyse and how to analyse, what to consider, how to operationalise questions, what methodology to use, *unit of analysis* is at the same time a problematic but also an important decision to make. Overall, there is no universal unit of analysis, as it always is shaped by the purpose of the researcher and the subject of study, so it should be appropriate for the purpose (Matusov, 2007), at the same time it has to be manageable for analysis (Lefstein & Israeli, 2015). Therefore, this chapter establishes what is the appropriate unit of analysis for interactions in online and physical spaces.

Unit of analysis as a notion, often causes confusion and the construct "unit of analysis" is mainly used for the methodological critique of others (Matusov, 2007). By definition, the *unit of analysis* can refer to data categories or theoretical categories (Timberlake & Ragin, 1989), or *"to the objects or things described by the variables"*(Remler & Ryzin, 2014). On a practical and methodological level, another confusion starts between the notions of *Unit of Observation* and *Unit of Analysis*. Unit of analysis is the "entity of analysis" — an analytical unit that conclusions are based on. Unit of observation is what we observe, measure, or collect. To sum up, the unit of analysis is determined by the research question, and unit of observation by data collection method ("Units of analysis and units of observation," 2016).

There are holistic and reductionist *units of analysis;* holistic approach argues that the unit has to express a whole phenomenon, while reductionist approach breaks the unit of analysis down to its *most fine-grain unit* (Matusov, 2007). Stahl (Stahl, 2015) overviews several philosophical paradigms and offers a typology of *the unit of analysis in cognition*, that are: concepts (Plato), observable physical objects (empiricism), mind's structuring categorization efforts (Kant), mental and material objects (Descartes) (and the relationship between them). All of the approaches dealt with the inner functions of the individual mind. According to Stahl, Hegel was the one changing the unit of analysis from the individual mind to social context.

As for theories and fields applicable/related to TEL: to Vygotsky it is a "self-contained" "unified smallest whole"(Vygotsky & Minick, 1987); To Leftsein (Lefstein & Israeli, 2015) unit of analysis is "discourse move" and dialogical. Though, Lefstein also suggests that aside from the appropriate phenomenon, the unit of analysis has to be expanded to the *sequence*. To Action-Network Theory, the main unit of analysis is embedded in the relationship between the actions (Latour, 1989) and its cognition is dialogic, so subjects cannot be studied alone (Bakhtin, McGee, Shepherd, Emerson, & Holquist, 2007). According to Stahl, Computer-Supported

Collaborative Learning field acknowledges social influences but focuses on the individual mind as a cognitive unit of analysis by controlling for these external influences (Stahl, 2015). Engeström (Engeström, 2014) is the one taking the unit of analysis to the whole activity system.

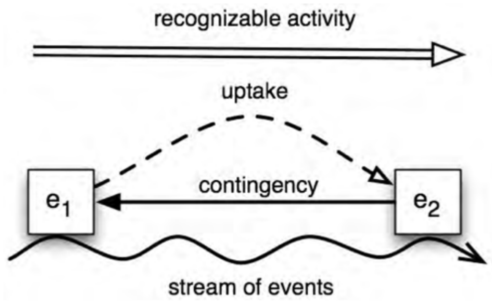


Figure 2 The unit of analysis in uptake framework, from (Suthers & Rosen, 2011)

Out of all the suggested units of analysis that may apply to TEL, I distinguish Suthers (2010) with his *Uptake Framework.* The author proposes that the *event is the smallest unit of analysis (Figure 2)* if we want to analyse data in a hierarchical manner and understand which interactions lead to learning, as already underlined in the previous section (uptake of knowledge). Also, the authors of Knowledge-Learning-Instruction Framework view *learning event* as the main unit of analysis (Koedinger, Corbett, & Perfetti, 2012). In this thesis, I adopt the *even*t as the unit of analysis, as proposed by Suthers and Koedinger among other authors, for several considerations: first of all, it is the smallest and holistic unit of analysis (Matusov, 2007) expressing the *dyadic* phenomenon of learning interactions involving all the necessary components (actor, verb, object) in its unit of observation, which makes it the most appropriate unit for its purpose (Matusov, 2007), second, it allows for a hierarchical analysis between separate acts (Latour, 1989). Third, this choice is also justified by the need for alignment of research paradigms, since my thesis aims for the analysis of learning interactions in physical and online spaces. Last but not least, one important factor is the technological landscape: to record and analyse learning interactions in physical space, technological specifications are needed (detailed in chapter 2.4.3).

2.4. AUTOMATED AND HUMAN-MEDIATED OBSERVATIONS: DATA COLLECTION AND ANALYSIS

While I already overviewed the paradigmatic issues on different research methods (traditional and automated) of data collection and analysis in chapter 2.2, contextualised the research in learning interaction analysis, in the following chapters I will continue to examine the issue further from data collection and analysis perspective; first, I will contextualise the discourse within automated and human-mediated data collection methods and overview the benefits and shortcomings of each of the approaches. Then I will demonstrate how automated and human-labelled observation data collections can complement each other. Finally, I will shift the discourse to other shortcomings of LA which is contextualisation and sensemaking of digital data.

2.4.1. MMLA observations: data collection

From the TEL perspective, learning happens in an increasing number of spaces using different tools and technologies (Martinez-Maldonado, Hernández-Leo, & Pardo, 2019) and involves different modalities (Worsley et al., 2016). To analyse these processes, data collected with/from different modalities, tools, spaces and collection methods are required. Observations, as a traditional method, have been used for decades to study educational processes and they have been mainly mediated by humans. Current teaching and Learning Analytics (LA) methods and tools provide automated means to assist the process of data collection and analysis or to gather data on digital interactions. LA can also be viewed as "modern" data gathering and analysis technique that support the observational process, either by reducing the workload (thanks to the automation of the process) or enriching the datasets with data coming from digital spaces (Rodríguez-Medina, Rodríguez-Triana, Eradze, & García-Sastre, 2018) (Macfadyen & Dawson, 2012). So, the synergy of human and automated observations could offer a complementary and multimodal view of educational contexts across spaces.

LA as a field stems from other fields like information science, sociology, psychology, statistics, machine learning, and data mining to analyse data collected during education administration and services, teaching, and learning. LA promises to have an impact on learning processes through the insights derived from the collected large amounts of data from authentic learning environments (Shibani, Knight, & Shum, 2019). LA creates applications that directly influence educational practice (Bienkowski, Feng, & Means, 2012) and based on the techniques from statistics, artificial intelligence and education management tries to determine how to assist learners, and improve the educational processes (Duval et al., 2017). As defined by the Society of Learning Analytics Research (SOLAR): *"Learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs".* LA studies use different sources, such as learning content, artefacts produced by the students, discussions, student profiles. Also, some traditional methods of data collection can be deployed alongside with LA sources: questionnaires, interviews etc (Papamitsiou & Economides, 2014). As initial trends of LA were mostly log and computer interaction data-driven and focused on prediction of performance and retention, reflection and awareness, feedback, assessment services and recommendations (Papamitsiou & Economides, 2014) and often uses non-statistical methods and surveys together with classical analytics techniques (Li, Lam, & Lam, 2015).

Among the different challenges that the LA community faces, the lack of evidence to understand and support teaching and learning practices is one of them (Giannakos et al., 2018). Recent reviews also reveal that the field of LA mostly relies on interaction traces automatically captured from a specific educational system while the data should be also gathered from educational contexts supporting multimodality and mobility to shape a holistic picture of how, when and where learning occurs (Martinez-Maldonado et al., 2019) (Papamitsiou & Economides, 2014). This need is amplified if we consider that teaching and learning tend to happen across spaces.

There are different ways one can collect learning data to enrich the evidence base and gain a deeper understanding on learning processes: cameras, wearable sensors, biosensors, infrared imaging, eye-tracking and more (Blikstein, 2013)(Ochoa & Worsley, 2016). Thus, to tackle the issue of the "street light effect" bias (Ochoa, 2017)(Freedman, 2010) that focused only automated and computer-mediated contexts, the subfield of LA, Multimodal Learning Analytics (MMLA) has emerged. MMLA uses and triangulates data collected from non-traditional as well as traditional forms (Worsley et al., 2016) and combination of these data sources enables the connection between digital and physical processes (Di Mitri, Schneider, Specht, & Drachsler, 2018). MMLA data such as eye-tracking, electroencephalography (EEG) is more reliable data-source compared to the clickstream data to predict learning performance (Giannakos, Sharma, Pappas, Kostakos, & Velloso, 2019), still, many challenges remain such as how MMLA data relates to learning and achievement of goals and how to combine human and machine interpretations of multimodal data (Di Mitri et al., 2018).

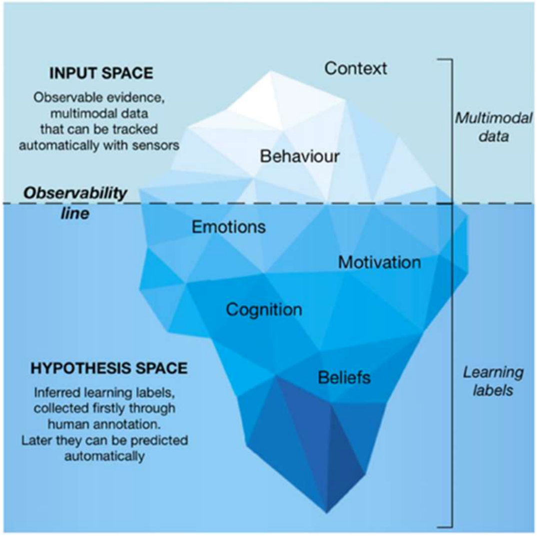


Figure 3 The observability line: the multimodal data can only capture observable attributes (Di Mitri et al., 2018)

Di Mitri et al (Di Mitri et al., 2018) distinguish between *input space* (data detectable through automated means) and *hypothesis space* (data that needs inference and interpretability) (Figure 3). These two spaces are separated by observability line denoting the space that can be observed through automated means and the space needing human-driven learning labelling to generate a hypothesis space. To address the limitations of automated means, observers can contribute to gathering evidence and interpretation of what is happening, especially in the physical world (Rodríguez-Medina et al., 2018).

Human mediated classroom observations (CO) traditionally serve a purpose of understanding teaching and learning processes and can be used to understand an on-going process or situation (Marshall & Rossman, 2014). One should not forget that this usually happens in a busy classroom life (Wragg, 2013) for teaching inquiry and research purposes (O'Sullivan, 2006). This traditional educational research method collects data from authentic settings based on the external observer views shedding light on different areas of interests. As some data collection methods (surveys, interviews) target participant views, classroom observations can provide a "*non-judgmental description of learning events that can be analysed and given interpretation"* (Moses, 2001). CO can gather data on individual behaviours, interactions, or the physical setting by watching *behaviour*, *events*, *artefacts* or noting *physical characteristics* (Marshall & Rossman, 2014).

There are some beneficial aspects of human observation: It allows for studying the events or interactions unfolding in a naturalistic setting; It is mostly unobtrusive in terms of data quality – observer acts as a recipient of information and data; Observations can provide a detached window into people response and interaction; They allow for inductive analysis for exploration of new phenomena; Observational research can offer unique data to study an ongoing process; Observations are usually used with other methods for data collection, where they fail in *"circumstances in which surveys, interviews, and experiments are simply insufficient or ineffective* (Bryant, Liebeskind, & Gestin, 2017) since self-report can be unreliable; Observations can be collected also by mechanical (i.e. automated means); they can collect not only verbal but also nonverbal information.

As for the weaknesses of observational methods, these are – Observer bias; The need for careful guidance for collection of validated and reliable information; If conducted overtly, they can cause "Hawthorne effect", pushing participants to behave differently; Access to population or setting might become a problem; Difficulty of replication can lead to generalisability issues; Last but not least, observational research can be very expensive and time-consuming, thus pushing the researchers to conduct smaller-scale projects (Bryant et al., 2017).

Observational methods can be situated on the continuum from structured to unstructured data gathering and analysis, where semi-structured data gathering lies in between (Cohen, Manion, & Morrison, 2007) (Bakeman & Gottman, 1997). This means that structured (systematic) observations produce quantitative data. In the case of structured observations, the focus of observations and its protocol is highly predefined together with the coding template and foci of interests. These points of interest (or foci) can include highly objective observations, for instance, physical movements, or more subjective inferences such as the consequences of events or relational dynamics (Ostrov & Hart, 2013). Unstructured observations are mostly exploratory and inductive, while semi-structured observations are between these two approaches. As inductive CO benefits from qualitative and unstructured data gathering (Marshall & Rossman, 2014), “unfocused” observations enable detecting emerging patterns of *events* or *behaviours* (Delamont, 2001). This type of data gathering though, may result in big volumes of unstructured data (Gruba, Cárdenas-Claros, Suvorov, & Rick, 2016). While reducing expressivity, systematic (structured) observations allow for more efficient analysis and data processing (Bakeman & Gottman, 1997). At the same time, it is advisable to have a focus and goals of observations even if its open-ended. Observations also can be indirect, which implies studying both verbal behaviour and textual material, produced by the participants in a study (Anguera, Portell, Chacón-Moscoso, & Sanduvete-Chaves, 2018). Observations are mainly analysed through codification, that can be *physically-based* or *socially-based* i.e. making inferences on behaviour, while the sampling techniques can be *time-oriented* or *event-oriented* (Bakeman & Gottman, 1997).

Total or partial automation of the observations is possible due to advances in technology (either during the data gathering or the analysis) (Anguera et al., 2018) (Bryant et al., 2017). This contributes not only to reducing the observation workload, but also to the improvement of the data quality and, finally, the trust and added value of the analysis (Pardo, Ellis, & Calvo, 2015). Computer-assisted observation can help the process of CO through enforcing specific coding schemes thus contributing to the quality, speeding up the process of observations (Kahng & Iwata, 1998), and enhancement of validity and reliability of data (Ocumpaugh et al., 2015). Computer-assisted systematic observation tools can help record interactions to study social dynamics at work (Klonek, Hay, & Parker, 2018), annotate emotions from audio and video for multimodal analysis (Böck, Siegert, Haase, Lange, & Wendemuth, 2011), study student emotion and behaviour (Ocumpaugh et al., 2015) etc. It is worth noting that most of the abovementioned tools are based on specific coding schemes or specific dimension of data (for instance, emotions) or theories (social dynamics), some have 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 (explained further in section 2.4.2).

Examples of the use of human-mediated classroom observations in combination with LA have been already reported in the literature, e.g., for teacher orchestration, to triangulate digital traces (Rodríguez-Triana, Martínez-Monés, Asensio-Pérez, & Dimitriadis, 2015), to observe technology-enhanced learning (Howard et al., 2018) and to evaluate their TEL proposals (Govaerts et al., 2018), or to collect meaningful learning interaction data (James et al., 2019). Moreover, HMO is more often used in combination with LA data, than combined with MMLA (Mangaroska & Giannakos, 2018). In this thesis, I argue that the complementing data-sets and aligning HMO and AO by developing conceptual and technological tools can increase data validity and availability. At the same, time HMO can further contextualise AO by introducing meaningful learning constructs and semantics in the data-sets.

2.4.2. LD and Contextualisation: data analysis and sensemaking

Some of the early identified issues in LA are pedagogically meaningful and actionable data analysis, sensemaking and reporting (Jivet, Scheffel, Drachsler, & Specht, 2017) and contextualisation of learning, evaluation and the interpretation of the results within the particular educational context (Papamitsiou & Economides, 2014)(Kirkwood & Price, 2014). However, as educational systems are contextual, different factors such as pedagogical design, actors, learning settings, used resources and tools come into play (Shibani et al., 2019). Thus, it may be difficult to make sense of the data available without knowing the context of learning, especially when using technological tools (Lockyer, Heathcote, & Dawson, 2013). Some authors have suggested the adoption of theory-driven approaches to obtain meaningful analytics (Gašević, Dawson, & Siemens, 2015; Rodríguez-Triana et al., 2013). However, it does not guarantee that the interpretation of the data would match the reality of the learning context and could inform educational practices.

Learning design *is "the creative and deliberate act of devising new practices, plans of activity, resources and tools aimed at achieving particular educational aims in a given context"* (Mor & Craft, 2012). According to Laurillard, learning design is based on a sequence of learning activities within which learning interactions take place (Laurillard, 2013). The information gathered inside of learning design (e.g., actors, roles, activities or resources) could contribute to the contextualisation of the data analysis (Lockyer & Dawson, 2011). Definitions of design can vary, referring to the *educational field*, the *artefact* that contained the design decisions or *the process of* designing the artefacts. (Dobozy, 2011). This thesis mainly focuses on the learning design (LD) as an artefact. I define LD as a *deliberate selection and design of learning activities reflecting teacher intentions and educational goals, that consist of (inter)actions with and between actors, digital or physical tools, and artefacts.*

LD or script can be used for the focused or guided data collection (Rodríguez-Triana et al., 2013). The use of LD is still an emerging approach towards contextualisation of data analysis and sensemaking (Lockyer et al., 2013)(Hernández-Leo, Rodriguez Triana, Inventado, & Mor, 2017)(Hernández-Leo, Martinez-Maldonado, Pardo, Muñoz-Cristóbal, & Rodríguez-Triana, 2018). Research has indicated a synergetic relationship between LD and LA from another perspective, where evidence informs LD as a *process* or *artefact* (Mangaroska & Giannakos, 2018). Such synergy would address the practitioners' need with the guidance for tested designs that support effective learning (Goodyear & Retalis, 2010).

While LD is a useful tool for data analysis and sensemaking, several issues must be taken into consideration: LD as an artefact needs to be created by a teacher, documented in a digital format and be accessible and interpretable by LA tool(Rodríguez-Triana et al., 2013). However, as the literature indicates, there can be several problems challenging this approach: (to some extent) limited adoption of learning design practices (Dagnino, Dimitriadis, Pozzi, Asensio-Pérez, & Rubia-Avi, 2018; Mangaroska & Giannakos, 2018) and the lack of authoring tools that provide access to the LDs and the usage of LD proprietary formats (Hernández-Leo, Asensio-Pérez, et al., 2018).

Besides, the field of MMLA often uses human-mediated learning labelling to make sense of the data (Worsley et al., 2016)(Di Mitri et al., 2019). Thus, contextualisation can also happen through human-mediated observations that traditionally provide highly contextualised data. Human observation and analysis have the innate ability to situate, contextualise and interpret the multimodal data that is emerging from a given learning scenario (Worsley et al., 2016). So, in simple words, human-mediated observations can drive contextualisation, especially, if LD is not available, or provide more contextual information.

2.4.3. Technological infrastructure and further methodological considerations

To enable multimodal interaction analysis through multimodal observations, aside from methodological issues like the *unit of analysis*, the conceptualisation of interactions and data collection methods, there is also an interoperability issue. To aggregate data, in a meaningful manner, I refer to xAPI[2], widely adopted standard that relies on a common syntax and has a potential to gather data not only from distributed networks but also from physical interactions. xAPI or Experience API is a specification that provides a format to model statements (typically learning experiences but could be any experience) that can be submitted by tool providers to a Learning Record Store (LRS). The Experience API is dependent on Learning Activity Providers to create and track learning. Learning Activity Provider is a software object that communicates with the LRS to record information about the learning experience.

The learning activity is a unit of instruction, experience or performance that has to be tracked. A statement consists but is not limited to the following syntax: *actor, verb, object, with result, in a context* to track an aspect of a learning experience. Actor data is unique information that describes a specific subject, such as a student or group of students. Verb data classifies the type of activity the actor participated in and often links to a human-readable description of the *event.* Object data will link to an artefact that is typically a by-product of related the activity or the agent/group (actor). At the same time, it has the potential to contextualise analysis through additional information and is flexible for different data collection needs: "*While the xAPI has predefined properties to include additional information such as context (context) and assessment data (results), the specification is designed to be extensible for unforeseen data collection needs*" (Kevan & Ryan, 2016). xAPI activity statements very closely follow the English syntax (or syntactic structures of many languages) contributing to making the statements more human-readable.

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

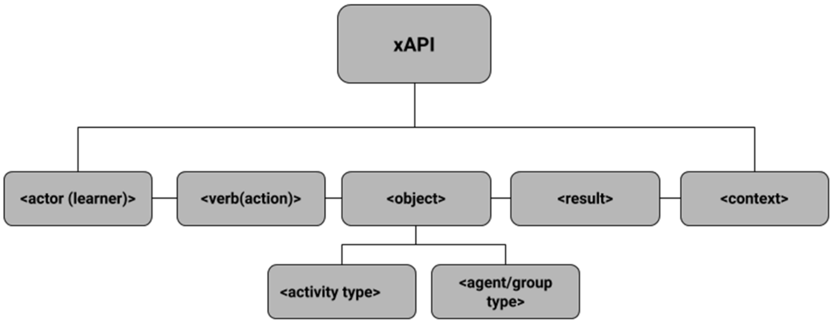


Figure 4 The standard structure of xAPI statement outlining its main elements

While believed that xAPI statements are inherently aligned with constructivist approaches, and specifically, with *activity theory* (Bakharia, Kitto, Pardo, Gašević, & Dawson, 2016; Kevan & Ryan, 2016), due to the specification's *object*, it is worth noting that this is debatable. The essence of *"object"* was misunderstood due to mistranslation; the "object" does not always mean *"object of activity*"(Kaptelinin, 2005); At the same time, the specification itself defines the object types that include *activity* and *agent/group* (actors, including grammatical objects) types. This means, that while it is definitely biased towards constructivist approaches, it can potentially contain and introduce different taxonomies and constructs including but not limited to *activity theory*. For this reason, xAPI is able to collect interaction data also with other semantics.

2.5. SUMMARY

This chapter has reviewed four main areas related to this PhD, eliciting challenges and needs to be addressed. Based on the methodological, philosophical and theoretical discussion on learning interactions and *unit of analysis*, contextualisation of data sources and data analysis, in this thesis I argue that in hybrid TEL settings, learning interaction data collection should be focused on *learning event*s as *the unit of analysis.* Then the data on them can be systematically collected by observing *learning interactions* in online and physical settings, which consist of *actor*, *action* and *object in a context*. In this thesis, I also argue that the collected data, aside from being merged and analysed together, needs to be contextualised. The main argument for *Contextualised Multimodal Observations* in this thesis is based on the following factors: *philosophical and methodological standing* (research paradigms), *technological infrastructure* (multimodality, syntax and interoperability issues), *theory and pedagogy* (from "clicks to constructs") (Knight & Buckingham Shum, 2017) i.e., semantics). The following chapters will demonstrate how this argument has been developed in the present thesis.

The following list synthesizes the research problems identified in the literature:

1. TEL, blended learning/teaching and learning across spaces:
   1.1. Problem: teaching and learning processes that happen increasingly in hybrid spaces need mixed data sources to analyse these processes
   1.2. Problem: gathering evidence with different methods and sources of data is difficult from such blended context
2. Educational research and practice in TEL:
   2.1. Problem: the methodological dichotomy between LA (modern) and CO (traditional) research paradigms hinders their alignment.
3. Learning interactions across spaces (automated and human-mediated data-collection):
   3.1. Problem: there is a need for systematic collection of data to align physical and digital space interactions (AO and HMO)
   3.2. Problem: there is a need for the definition of the unit of analysis and technological infrastructure for systematic collection of across spaces interactions (AO and HMO)
4. MMLA and contextualisation of automated data
   4.1. Problem: there is a need to address the "street-light effect" often present in LA for meaningful analytics
   4.2. Problem: there is a need for guided collection, contextualisation and sensemaking of learning interaction data in authentic contexts

These problems led me to the following main gaps:

1. Lack of support for contextualisation for sensemaking and analysis of MMLA observations
2. Lack of conceptual and technological tools to connect HMO and AO

As introduced in the PhD diagram (Figure 1), these research problems and gaps identified led me to the formulation of the main research questions of this thesis (stated in the upcoming section).

3. RESEARCH PROBLEM AND QUESTIONS

Based on the problems and research question outlined in the main diagram for the PhD research in chapter 1 and the literature overview in the previous chapter, in this chapter, I will contextualise the research problem and gaps this PhD thesis is responding.

Based on the literature review and identified research problems (detailed in chapter 2), I argue: to inform educational research and practice that increasingly takes place across spaces there is a need for holistic evidence, contextualisation of data analysis or triangulation of the findings. Data on learning interactions can be gathered through several traditional or modern data collection methods. To inform teaching and learning practices in the classroom, observational methods (manual or automated) have been frequently used combining other data sources (such as surveys and interviews). At the same time, aside from complementing data sources, there is a need for guiding the data collection and contextualisation of the analysis, which can happen through LD or highly contextual human-mediated observations. Therefore, there is a need to establish a synergetic relationship between learning design (as a field of research) and MMLA classroom observations. For its implementation on a practical and theoretical level, conceptual and technological tools are needed.

To collect the interaction data from both physical and digital settings and align it with LD for contextualisation, several methodological, conceptual and technological considerations need to be taken into account, i.e. *the unit of analysis* should be defined and the data collection should be modelled accordingly. So, based on the short overview of the research problems, I have defined the main research question:

How to align Human-Mediated (HMO) and Automated Classroom Observations (AO) to enrich data-sources and contextualise the data analysis in blended learning?

To answer the main research questions, 4 sub-questions were posed which have been tackled in different papers of this PhD:

RQ1 What conceptual, technological, methodological considerations and unit of analysis should be taken into account for pedagogically grounded and theory-driven data collection and analysis of across-spaces interaction data? **(I, II, III)**

RQ2 What are the technological and conceptual tools needed for context-aware MMLA observational data collection? **(IV, V)**

To answer the RQ, one additional step was needed to understand the *process*, *elements*, and *motivation* of data collection for different stakeholders.

RQ3 How can LD aid the data collection and analysis in blended learning scenarios? **(VI)**

RQ4 How can CO aid the data collection and analysis in blended learning scenarios? **(VII)**

Table 2 Summary of the problems (defined in chapter 2.5) and connected research questions per article

Article	Problem	RQs	Article question
I	3.2; 4.1; 4.2	RQ1	*What are the technological and theoretical considerations and unit of analysis for theory-driven data collection and analysis of learning interactions in online settings?*
II	1.1; 1.2;3.1	RQ1	*Is it feasible to collect learning interaction data from classroom observations with the event as a unit of analysis and in xAPI format using a classroom observation app?*
III	1.1; 1.2	RQ1	*How to Aggregate Lesson Observation Data in LA datasets?*
IV, V	1.2; 2,1; 3,2; 4.1; 4.2	RQ2	*How can we integrate classroom observations to generate semantically annotated, context-aware data in multimodal data sets?* *What are the process, elements, and motivation of different stakeholders and unit of analysis for observational data collection?*
VI	2.1; 3,2; 4.1; 4.2	RQ3	*How have other researchers used classroom observations and aligned with LD?* *What are the important open issues and future lines of work?*
VII	1,2; 2.1; 3,2, 4.1; 4.2	RQ4	*Which aspects of digital-trace based LA could benefit from observations?* *What is the added value that **observations** offer to the user in terms of meaning, context and quality?*

4. METHODOLOGY AND RESEARCH DESIGN

4.1. METHODOLOGICAL CONSIDERATIONS

Main research problems and question as identified and defined in previous chapters led me to the main question of this research: *how to align Human-Mediated (HMO) and Automated Classroom (AO) observations and Learning Design (LD) to enrich the data-sources and contextualise the data analysis in blended learning?* Thus, the main objective of this research has been defined as *Alignment of Human-Mediated (HMO) and Automated Classroom Observations (AO) and Learning Design (LD) to enrich the data-sources and contextualise the data analysis in blended learning*. In line with the research questions and objectives, a clear need for conceptual and technological tools was identified. This led to the need for the development of two main contributions of this thesis - the Framework for Contextualised Classroom Observations and CO app Observata. To accomplish my objectives and deliver contributions, that implies designing innovation in TEL requiring a synergy between researching, designing, and engineering (Wang & Hannafin, 2005), having adopted pragmatism as a philosophical approach, I have followed an interpretative research paradigm (Cohen et al., 2018). In line with paradigm philosophy, I have chosen to follow design research tradition as it is a *"systematic but flexible methodology aimed to improve educational practices through iterative analysis, design, development, and implementation"*(Wang & Hannafin, 2005). Ejersbo et al note (Ejersbo et al., 2008): *"In practice, though, this research process can be unbalanced and end up with an emphasis on either the design process or theory development. In a professional production environment, there typically will be a strong focus on finishing a product and not necessarily on generating theoretical insights*". Therefore, balancing between the theory development and design is equally important.

DBR and RBD are two similar yet distinct research approaches that aim for evidence-informed design and development practices. Design-Based Research (DBR) is a pragmatic approach (Barab & Squire, 2004) that aims to achieve changes by creating theory and formatively evaluate it. DBR offers a research framework that allows for a holistic and comprehensive investigation into complex and novel learning situations that lack usable theoretical basis (Bannan, 2009). Although RBD does not exclude the development of the theory through the design activity, the main difference between them is the focus on design artefact as the final output; in Research-Based Design (RDB) *"the result of design is a product: design as a noun"* (Leinonen et al., 2008). However, even if the focus on the design falls strong, the final design artefact still communicates the theoretical findings of the research. Some argue, that RBD lacks the rigour of DBR process (McKinney, 2014), therefore, in this research, I tried to balance between the "design as a process" (theory generation) and "design as a noun" by basing my theoretical claims on the research problems identified in literature in the first phase of the research (contextual inquiry (Figure 5) and iteratively revising and validating these claims through and by building the design artefacts. To my view, it this should not be a matter of dichotomy between research and design but rather, taking the best from these two similar approaches, which this thesis has attempted to do.

Out of different design methodologies that are defined as the most successful in TEL development as they address real-world challenges in authentic context, I have found RBD process (Leinonen et al., 2008) to be suitable as it is directed at development of artefacts as main contributions but at the same time, is research-based.

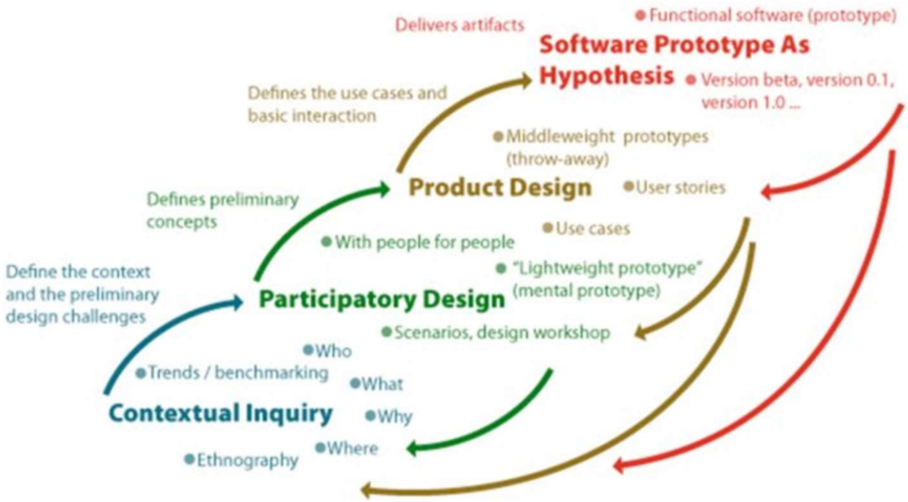


Figure 5 Research-based design process (Leinonen et al., 2008)

This research design spans through 4 phases: *contextual inquiry, participatory design, product design and software prototype as a hypothesis* (see Figure 5). While it is considered as one of the variants of design-based research methodology and stems from it, research-based design targets the development of innovation through participatory, iterative approaches (where iterations happen between these 4 phases) that tries to negotiate between participant's and researcher's views delivering main design artefacts as a hypothesis.

Based on the research questions and objectives that aimed to develop design artefacts, the overall research design has been more exploratory than confirmatory, more inductive, than deductive, for this reason, different research designs and data analysis methods have been used in different phases. The studies have been mostly qualitative (research methods for each phase and article, sample and analysis methods are detailed in chapter 4.2). Therefore, as indicated also in the RBD methodology, this research is not a hypothesis-testing study. It is rather a hypothesis-generating study that delivers a *hypothesis* in a form of design artefacts: specific Framework (consisting of 3 contributions) and the corresponding software prototype which are not considered a finalised product.

In accordance with the methodology, the research has been accomplished in several phases that are not necessarily detached from each other; corresponding articles report on its steps and smaller portioned objectives towards the goal in phases or stages (Figure 6). In some cases, research was going forward and at the same time, going back to the contextual inquiry phase to better understand the context and refine the Framework and the app. To answer the main research questions of this thesis, in line with its objectives, to develop the Framework and generate conceptual design of the software as a hypothesis and evaluate in authentic settings, I have followed the steps defined in Figure 6.

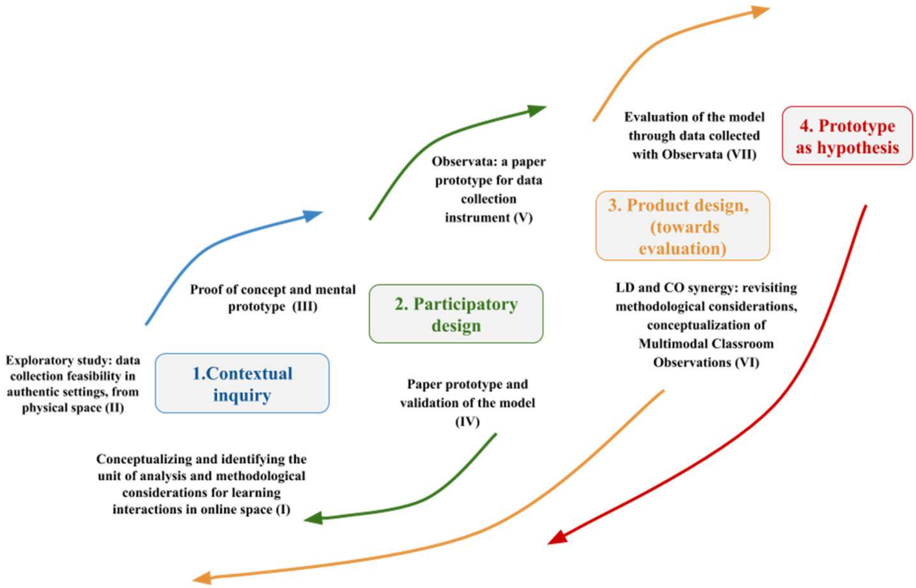


Figure 6 Distribution of articles within the RBD process summarizing main steps and phases (adapted schema from (Leinonen et al., 2008))

Though the Framework has been preliminarily validated in a participatory design session (**IV**) and then through a co-case study using Observata (**VII**), the Framework and corresponding software prototype that implements it, represent a hypothesis that are to be tested and evaluated further. Figure 6 summarizes the overall research timeline and its phases within the research-based design tradition.

1. Contextual inquiry: The contextualisation of this PhD entailed conceptualisation and identification of methodological lenses for data collection and analysis, the unit of analysis, and data collection format for online and physical interaction analysis. Also, a key aspect was to reflect on the feasibility of collecting the required data in the context of the study, in authentic blended learning settings. The outcome of this phase was the development of the mental prototype of the app and the first version of the Model (**I, II, III**).

2. Participatory design: The previous phase led us to participatory design phase using design sessions and scenario-based research through which I have validated the model (**IV**) and corresponding conceptual design and a paper prototype for data collection instrument (**V**). The outcomes of this phase are validated paper prototype of Observata and the Model. It is worth noting that the use cases for the participatory design session have been derived from the Estonian semiformal requirements for classroom observations, and the general teaching and learning practice with the widespread use of technology in the classrooms – in both contexts conceptual and technological tools were needed. Correspondingly, personas and scenarios had been derived from these practices, at the same time guided by the theory and research problems identified in the literature.

3/4. Modelling, towards evaluation and producing software as a hypothesis: In this phase, the software prototype has been produced and I have evaluated its applicability in authentic settings. These two phases of RBD are presented together as the final outcome was the design artefact and that communicated theoretical findings in the form of a final hypothesis for our research. Furthermore, in this phase I further examined the alignment between LD and CO and defined the need for alignment, conceptualizing modern (automated) and traditional data collection method and identified methodological considerations, needed infrastructure and challenges (**VI**), evaluating applicability of the framework in authentic settings through data collected with Observata (**VII**). The final outcome of this phase is the software prototype as a hypothesis.

4.2. RESEARCH DESIGN, INSTRUMENTS AND DATA ANALYSIS

The following table summarizes the articles' objectives, design and analysis techniques:

Table 3 Each article in the thesis contextualised in the research phase with objectives, design and data collection and data analysis methods

Phase	RQs	Article	Objectives	Design, data collection and sample	Data analysis
I	RQ1	**I**	Establishing learning interaction concept in online settings, theory-driven data collection and analysis (unit of analysis, format).	Literature review, conceptual proof of concept through a sample scenario.	N/A
	RQ1	**II**	Data collection feasibility from physical learning interactions through CO.	Desk analysis of requirements, an exploratory case study, classroom observations. Sample – 12 lessons observed (with 12 teachers), 2 researchers coding the data.	Open coding with event sampling.
	RQ1	**III**	Methodological considerations for (MM)LA Classroom Observations, creation of mental protype.	Literature review, proof of concept. Sample – 2 research studies.	Application of the concept through analysis of research studies.
II	RQ2	**IV**	Validation of the model and corresponding app mental prototype.	Scenario-based research, Participatory design session with a focus group. Sample - 6 teachers and researchers.	Content analysis, open and axial coding.
	RQ2	**V**	Paper prototype of the technological solution Observata.	N/A	N/A
III/IV	RQ3	**VI**	Aligning LD and CO, conceptualizing Multimodal Observations	Systematic literature review Sample – 24 papers	Content analysis: inductive and deductive
	RQ4	**VII**	Establishing the value of observations in MMLA and evaluation of the applicability of the framework in authentic scenarios though the data collected with Observata.	Co-design Case study: questionnaires, interviews, log data and observations. Sample – over 15 observed and 5+1 analysed lessons, co-design study sample with 2 project managers.	Data analysis and visualization by plotting data based on different metrics, Social Network Analysis, content analysis.

5. RESULTS AND DISCUSSION

In this chapter, each subsection reviews research problems, research questions and points out to the related papers where I have addressed them. Each subchapter is accompanied by a diagram explaining the research phase in focus and how articles are positioned within it. It also presents the contributions of the thesis and compile evidence collected along illuminating the emergent findings. While data collection and analysis methods are detailed in the previous chapter, methodological considerations are shortly discussed alongside the papers and contributions. Each subchapter is concluded by a short discussion on main contributions and conclusions.

5.1. PEDAGOGICALLY GROUNDED AND THEORY- DRIVEN LEARNING INTERACTION DATA COLLECTION AND ANALYSIS ACROSS SPACES: THEORETICAL, TECHNOLOGICAL AND METHODOLOGICAL CONSIDERATIONS

This phase is mostly based on the literature overview where I have established a theoretical background, identified first research problems and gaps and laid a conceptual and methodological ground for thesis contributions. Most of the claims and discussion are based on this literature review, illustrated with two conceptual papers (containing proofs of concept) and one exploratory case study. Thus, the phase I is based on the research problems identified by the research communities in different research lines already detailed in the introductory part of the thesis. These research problems (RP1.1; 1.2; 2.1; 3.1; 3.2; 4.1; 4.2) concern the increasing need for mixed data from blended learning contexts (Mor et al., 2015) and difficulty gathering evidence (Oliver & Trigwell, 2005); dichotomy of research paradigms (Daniel, 2019); need for interaction data for the analysis of blended learning contexts (Drysdale et al., 2013); the need for contextualisation of LA data (Shibani et al., 2019) and theory-driven analysis (Gašević, Dawson, & Siemens, 2015; Rodríguez-Triana et al., 2013); as well as the enrichment of LA data sources with across spaces data in blended learning contexts, are still problematic in the field of LA (Ochoa & Worsley, 2016)(Freedman, 2010)(Blikstein & Worsley, 2016); and methodological issues such as unit of analysis for interactions (Suthers & Rosen, 2011). All of this led me to the creation of the methodological and theoretical basis for guided data collection and analysis of across-spaces observational data.

Thus, this chapter covers the phase I of this research, that represents contextual inquiry and answers to the following question:

RQ1 *What conceptual, technological, methodological considerations and unit of analysis should be taken into account for pedagogically grounded and theory-driven data collection and analysis of across-spaces interaction data?* **(I, II, III)**

This research question is divided between conceptual, methodological and technological parts and is answered accordingly throughout this chapter, at the same time delivering the first contribution of the thesis. Covering different educational contexts, spaces (digital and physical) and research problems rooted in different disciplines increased the complexity of this research. Therefore, the phase I was more extensive and theoretical than others. This is directly reflected in the publications **I, II, III** (Figure 7) which informed the phase II (participatory design). Since, according to this research methodology, the phases of research are not completely detached from each other, aside from their direct aim, some publications also reflect and come back to contextual inquiry phase (for instance, publications **IV** and **VI**), because ideas were becoming clearer with design activity. For the sake of clarity and main research aims, in this chapter, I am covering only the articles that directly deal with contextual inquiry phase establishing the context of this research through a theoretical overview, proofs of concept and exploratory research study in authentic settings.

With 3 publications covering different research questions I have established theoretical and methodological considerations for online and physical learning interaction analysis, tested the feasibility of coding learning event as unit of analysis in authentic classroom settings, introduced the concept of pedagogy-aware data-collection and based on the literature review and identified research problems, developed a mental prototype of an app that connects this phase to the phase II that aims at the development of the conceptual and technological solutions with participatory approaches. The publication **I** posed questions such as *what analytical frameworks and technological solutions could be put in place for multi-level, multi-theoretical analysis of distributed learning interactions.* Publication **II** focused on whether *is it feasible to collect learning interaction data from classroom observations with the event as a unit of analysis and xAPI format using a classroom observation app?* And the publication **III** answered the question on *How to aggregate classroom observation data in LA datasets?*

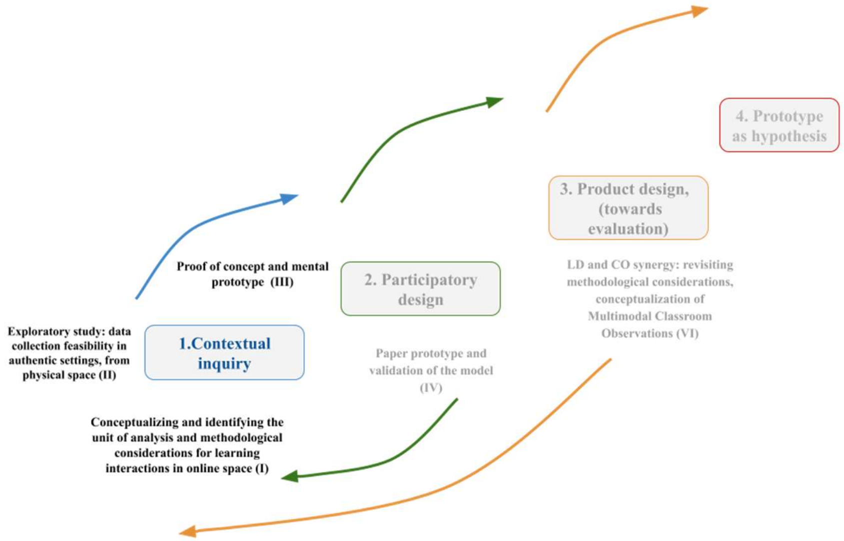


Figure 7 Articles I, II, III dealing only with contextual inquiry, partly going back to contextual inquiry **-** IV, VI

To understand how physical and digital interactions could be modelled using common LA lenses, learning interactions were conceptualised within the context of an emerging field of LA, reflecting on its analytical frameworks and the choice of the *unit of analysis* (publication **I**). This publication focused on theory-driven learning interaction analysis in online, distributed learning settings and represents a literature review and a proof of concept with hypothetical scenarios

Conceptual considerations: based on the literature review, I established that *Uptake Framework* (directed at interaction analysis in distributed settings) would be suitable analytical lenses, redefined the concept of learning interactions within the field of LA, defined the unit of analysis for learning interactions and related it to technological infrastructure (xAPI – specification that can record learning experiences/learning interactions in distributed settings). The suggested *Uptake Framework* analyses interactions based on learning events in a hierarchical structure, i.e. it is interested in analysing relations between interactions focused on the *event* as the unit of analysis (Suthers & Road, 2015). So according to the results of the literature review and theoretical inquiry, coupling learning interactions concepts with *Uptake Framework*, unit of analysis as a *learning event* and xAPI provides with the following:

1. Interaction should be recorded as dyadic events (as defined in the Uptake Framework in table 1)
2. The relations with domain (theory, learning constructs) should be already identified through annotations (mainly verbs), entities and their relationships can be established and recorded through xAPI statements.
3. Learning activities and actions happening outside the LMS should be also recorded through xAPI specification, so it will support the concept of distributed interactions.
4. Pedagogy and theory-driven learning interaction analysis can be automated based on the point stressed in 2.

This conceptual proposal has been illustrated through a hypothetical scenario in online settings as a proof of concept. Later on, has been further developed in this chapter, the validation of which been done in a design session described in chapter 5.2.

Scenario: This sample scenario takes collaborative concept mapping as a didactical method, domain ontology (verbs, learning theory) and is aligned with learning outcomes. Teacher gives an assignment to the students in an online platform, while explicitly connecting the assignment with a specific learning outcome. As each learning outcome is previously annotated with 2–3 keywords from the domain ontology, the platform connects all related learner interactions also with these keywords. In the given case, the assignment is: "Form the groups of 2–3 and identify core concepts related with digital competence and their relations, so that it would be compatible with three digital competence standards. Read the Chap. X from the course textbook and compare three digital competence standards. Submitted a concept map that includes an initial set of concepts". Student groups start working on the assignment in their personal learning spaces, the blogs that communicate to the BOS service of the platform all interactions. Each student separately identifies the set of concepts and reports about them in his blog, students can monitor each other's blog posts and comment each other's work – the goal is to come to agreement which concepts should be used in the concept map. In this phase some teachers like to comment students' blogs, whereas others don't intervene in the process and wait only for the final assignment result. Next, students start working with the shared concept map in a Web-based tool Bubbl.us, using this set of concepts, and they use Skype for discussing while they work. Final concept maps are submitted as assignments by each student group. Extended xAPI record for such interactions are documented in the following format: In <Context>, <User> performs <Action> on <Object> with <Tool> producing <Result> at <Time>. For instance, a specific line in the record might look like this**: In Assignment 3, John adds a comment to blog postX with toolX at 12:30 12-07-13.** All the xAPI records related to this assignment are then passed to the learning analytics module of the platform, which returns an overview of interactions, recommendations and feedback in the form of diagrams.

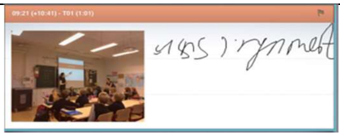
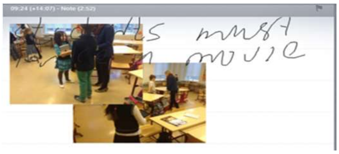
Thus, this conceptual approach answers to some of the research problems identified in literature concerning the contextualisation of data, theory-driven analysis (**RP4.2**) (Shibani et al., 2019) (Gašević, Dawson, & Siemens, 2015; Rodríguez-Triana et al., 2013) and definition of unit of analysis and technological infrastructure (**RP3.2**) (Suthers & Rosen, 2011) suggesting a flexible conceptual solution for automated, theory and pedagogy-driven LA systems.

Technological considerations: After establishing a framework through theoretical inquiry, I understood that it would be possible to apply the concepts introduced in the publication I in "offline settings" (publication **II**). I then tried to connect classroom observations with LA through the same unit of analysis for learning interaction analysis and xAPI specification. The publication has first, overviewed different classroom observation tools with pre-established requirements in accordance with analytical framework defined in publication **I**. Based on the overview of observation apps a specific observation tool (LessonNote)[3] was chosen since it met some of the requirements (for instance, it enabled open coding with open semantics, identifying subjects of interactions, and timestamping). An exploratory case study using observations on the use of e-textbooks in classroom settings allowed us to gather insights on the technological and conceptual requirements that a classroom observation tool had to have to collect LA compatible data from physical classroom. We observed 12 lessons in 6 different K-12 schools. These schools were chosen because of their more advanced IT infrastructure and teachers with innovative learning and teaching practices. To document the lesson flow and emerging interactions we used LessonNote application. LessonNote application allowed timing, recording photos of student work and activities, which were inserted into the

[3] http://lessonnote.com/

notes, and creating seating charts. Additionally, we video-recorded all the observed lessons. Two researchers have coded data according to xAPI statements. In this study, the collection of learning events (unit of analysis) through the simulated aggregation of xAPI statements was tested. Since LessonNote app did not allow establishment of connections with objects or introduction of verbs in computer-readable format, we ended up gathering the data the following way: we were able to choose subjects by establishing interactions only between subjects, timestamped them, manually taking notes within the app on verb and object parts. Main conclusions of this research were: it proved feasible to collect *xAPI statements* from physical settings by coding *learning events* (Table 4), thus, the concept was validated on a technological level. Furthermore, I concluded that for the systematic aggregation of xAPI events not only a new approach, but also a technological solution was needed– a new classroom observation tool had to be developed.

Table 4 Illustration of how observed events can be recorded as xAPI (RQ1)

Activities	Events illustrated in LessonNote	Video transcript recorded as xAPI: Subject-verb-object
Teacher activity		Teacher organizes class **Teacher gives assignment** Teacher forms groups
Group activity		Group A moves out **Group A organizes tools** Group A starts a discussion

By establishing the technological requirements of the app and the following framework, I have answered to the technological part of the research question, at the same time proposing solutions to the research problems concerning blended learning contexts and difficulty of gathering evidence from such contexts (**RP1.1; 1.2**); methodological dichotomy between research paradigms (**RP2.1**); and need for interaction data across-spaces (**RP3.1**) and proved the conceptual and technological feasibility of having the *event* as unit of analysis for data collection. To collect data from authentic context and physical spaces, I suggested using classroom observations to gather observable events with xAPI statements, illustrated and evidenced by the study (**II**).

Methodological considerations: For me, it then was still unclear that what I was attempting to establish (**II**) (i.e., gather data from "offline learning interactions" to align it with online learning interaction data), would turn into an MMLA-related contribution. Thus, this thesis was framed within the MMLA field for the first time in publication **III**, where I explored the *unit of analysis* from different dimensions resulting in the first version of the Model and mental prototype of the application.

Publication **III** is a theoretical proof of concept for the methodological considerations in observational data collection, validating the concept by applying it to 2 research studies. It proposed the first version for the *Model and the Protocol for MMLA Observational process*; an approach for data collection linked to the concept of a unit of analysis. Besides, this paper presents the mental prototype of Observata (conceptual design) (see Section 5.4) of a classroom observation app designed and developed to implement and validate the theoretical contributions of this PhD. As methodological considerations are one of the main contributions of this thesis, they are detailed in the following chapter.

5.1.1. Contribution 1 – Model and Protocol for Multimodal Observations

After defining conceptual and technological considerations, this chapter will report on one specific contribution. The first contribution of this thesis is the Model and the protocol for MMLA observational process; three dimensions are taken into account when developing the methodological framework (Figure 8):

- The philosophical and research approach that frames the purpose of the LA study;
- The educational theory and the pedagogical background that sustains the learning scenario;
- The technological and architectural aspects that condition the data gathering and integration of multiple and heterogeneous data sources;

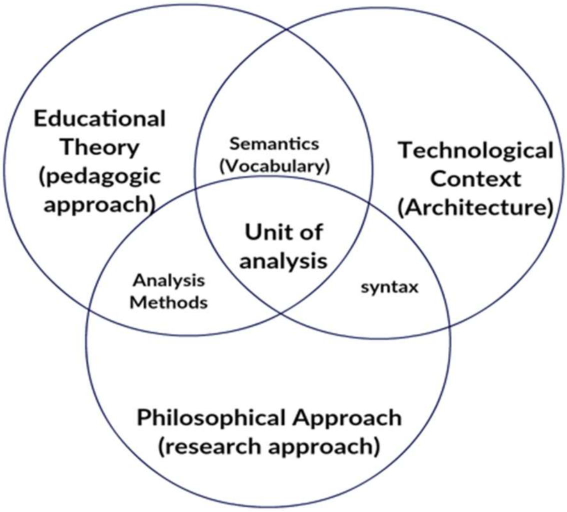


Figure 8 The model for contextualised MMLA observations (first version)

The suggested model for observation data process is an integrated view that answers to the challenge of **technological context -** lack of standards to integrate heterogeneous and multimodal data-sources (xAPI)(Kevan & Ryan, 2016), **theoretical dimension** - need for grounding with pedagogy and theory (semantics)(Knight & Buckingham Shum, 2017) and **philosophical/research approach** - different research approaches representing two paradigms for data gathering (human and automated observational data) as already defined by other researchers (Daniel, 2019). Figure 8 illustrates how the unit of analysis acts as a cornerstone in the intersection among three dimensions. To be compatible with all of them, the unit of analysis is modelled as pedagogically neutral, semantically open (vocabulary is interchangeable), and system-independent. In this way, this *unit of analysis* allows us to collect data with different pedagogical semantics and integrating them later on, with other data sources. The choice of this unit of analysis is dictated by the technological context and data standards (xAPI) on online settings that at the same time allows it to be human and machine-readable - *event* as the unit of analysis makes it possible to connect across-spaces data. This specific *unit of analysis* is one of the conceptual and methodological contributions of this thesis that constitutes the decisive element of all the contributions later. This choice has been based on different dimensions: *philosophical* (methodology), *technological,* and *pedagogical*. While there could have been other alternatives of the unit of analysis such as *individual*, *group* or *activity* they would not have been appropriate in terms of expressiveness and richness (semantics) for data collection and analysis, as well as for the abovementioned dimensions. In this approach, the learning event (unit of analysis) is expressed using xAPI statements. Based on the proof of concept, I have envisioned that the presented approach could be suitable for pedagogy-aware, real-world observational data collection, and it could serve a basis for the development of observational data collection solution in a form of classroom observation app. Results of this paper directly informed the participatory design (phase II).

I have established steps (protocol) for observation data collection detailed the table below (Table 5). These steps are meant first, to define the data gathering protocol contributing to the validity, systematization and rigour of data, ensuring the technological interoperability, at the same time, taking into account the learning context for guided data collection. Second, this protocol serves as a mental prototype of the envisioned app, reported in chapter 5.2.

Table 5 Steps of the multimodal observation protocol

Step	Description	Process
1	**Be aware of the elements that belong to the learning context**	To facilitate the data gathering (seen as an observer's task) and to enable integration, it will be necessary to register in all the actors and objects in advance. In that way, the observer will be able to link the events to the corresponding actors and objects. A first implementation challenge will be to know in advance not only about the actors and objects but also to extract the corresponding identifiers which are necessary for later integration and analysis across data sources. To solve this issue, some authors proposed to use the learning design and its instantiation in the technological environment as a description of the context. However, this solution is not flexible enough for learning scenarios where new participants or objects may emerge during the activities.
2	**Define the areas of focus**	Define the indicators to illuminate such areas, and the specific events to be observed. Observations are envisioned as a part of a multimodal dataset. Thus, it will be necessary to define, as a whole, how the different areas of interest are informed by the data sources available, and the trackable events. In the case of the observations, the application will be loaded with the vocabulary necessary to describe the events (xAPI verbs).
3	**Collect observable events**	The observations will be recorded following the *subject-verb-object* structure, using the set of previously loaded subjects, verbs, and objects. These events will be presented as xAPI statements that will be timestamped and sent to a learning record storage together with the rest of the multimodal dataset. It should be noted that a first study was already carried out to ensure whether it was feasible to register the observations following the aforementioned format.
4	**Analyse and interpret the results**	The observations will be analysed with the rest of the events tracked by the complementary data sources, extracting previously chosen indicators for the different areas of focus.

It is worth noting that the proposal was based on the literature review and the identified research problems. To illustrate the potential of the proposal, we have identified two research papers that make use of both observations and LA, evidencing its applicability in research contexts (Table 6). In this case, the steps defined in the MMLA observation process (Table 5) would help researchers and teachers systematically collect the MMLA evidence on the learning process, and interpret them according to the previously chosen indicators.

Table 6 Potential cases of application for the multimodal observation protocol (RQ1)

Case/Ref	Context	Target user/ Object of analysis	LA data source/tool	Observation type/tool	Aim
(Rodríguez -Triana et al., 2013)	Blended	Teacher/ Pre-defined event, interactions	Student logs from DLE/ GLUE!-CAS	Student observations, structured, contextualised in learning activities/Google Spreadsheets (transformed in a machine-readable format/integrated with other data sources	Reflection on the aspects to be evaluated in a learning scenario
(Rodríguez -Triana, Holzer, Prieto, & Gillet, 2016)	Blended	Observer/ predefined event, interactions	Teacher and student Logs from app/SpeakUp	Teacher and student observations, structured/manual	Evaluation of an app, triangulation of data

As previously identified in the literature, data gathering from physical contexts and their contextualisation is a challenging issue. To connect data from physical and digital settings, specific conceptual and technological tools are needed, that entail definition of methodological steps and protocols. This contribution addresses all the research problems reported at the beginning of this chapter and is a holistic answer to theory and pedagogy-driven interaction data collection and analysis across spaces. With this proof of concept, we concluded that in both cases, the proposal presented in this paper could be compliant with the processes, as well as the unit of analysis followed by the observer and teacher. Thus, it could potentially benefit these stakeholders in systematic data collection and analysis of MMLA observations. Therefore, the envisioned application could have contributed to automatization and simplification of the data gathering and integration processes. As for research implications, this methodological proposal can be useful for researchers and practitioners interested in the pedagogy-driven classroom observations and analysis in blended learning. Considering the practical implications, observers and teachers can use the steps defined in the proposal to collect the MMLA compatible data through observations. These implications of the proposal will be explored further in the following chapters showcasing other possible users and use cases. The empirical validation of the further version of this contribution in a participatory design session is reported in chapter 5.2.

Summary (RQ1)

In line with the research problems defined in the beginning of this chapter, namely: need for analysis of blended learning context and gathering evidence from such contexts; need for multimodal interaction data; need for alignment of CO and LA (dichotomy of research paradigms); contextualisation of LA data and theory-driven analysis; enrichment of data sources with across spaces data in blended learning contexts; and methodological issues such as the unit of analysis for across-spaces interactions, in this chapter, I answered the following **RQ1** *What conceptual, technological, methodological considerations (unit of analysis) should be taken into account for pedagogically grounded and theory-driven data collection and analysis of across-spaces interaction data?* To answer the research question I have established conceptual, technological and methodological lenses and evaluated them with proof of concepts and an exploratory study. Aside from this, in this chapter, the main identified users and use cases of the suggested contributions are a teacher (**I**); observer and researcher (**II, III**), covering teaching and research contexts. These contributions have been suggested and validated with a proof of concept and an exploratory case study.

Thus I have proposed: conceptualisation of analytical lenses for log data, conceptualisation and definition of analytical unit (**I**), establishment of technological considerations and feasibility of data collection for physical settings (**II**), definition of methodological considerations, and steps for MMLA protocol (**III);** All of this resulted in a mental prototype of the application (Table 5) and the Model and the protocol for MMLA observational process; (Figure 8) that informed the second phase: participatory design.

5.2. TOWARDS CONTEXTUALISED MULTIMODAL OBSERVATIONS: TECHNOLOGICAL AND CONCEPTUAL TOOLS

Informed by the research problems identified in the literature and the artefacts derived from phase I of the research, this section reports on the second phase of this research: the participatory design. As this phase also revisited the contextual inquiry, the problems covered in this phase are also revisited. Thus, the following research problems are covered in this subchapter: need for data collection from blended learning contexts; need for the alignment of methodological dichotomy of research paradigms; need for across spaces interaction data, addressing the issues of “streetlight effect” and contextualisation of data authentic learning contexts (RP1.2; 2.1; 3.2; 4.1; and 4.2).

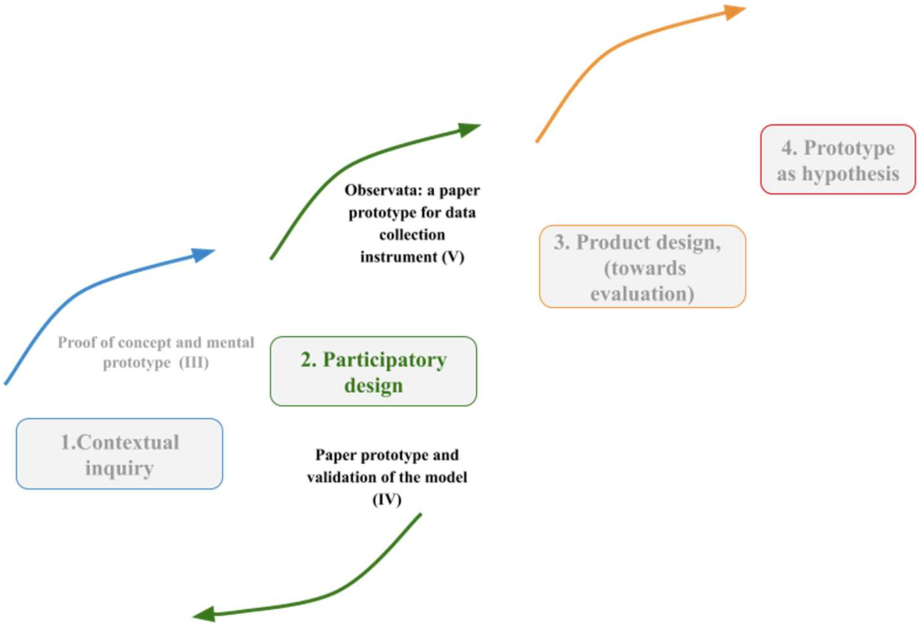


Figure 9 Phase II main articles and the connection to the phase I main artefact

This phase has been covered in publications **IV** and **V** and addresses specific research questions namely:

RQ2 *What are the technological and conceptual tools needed for context-aware MMLA observational data collection?* **(IV, V)**

This phase mainly covers the development and validation of paper prototype of technological tool (Observata app) and the *Model for Contextualised Multimodal Observations* needed for observation data collection (**IV, V**). As already mentioned in the previous chapter, this phase partly returned to the contextual inquiry to re-examine the theoretical basis of the Framework (phase I main artefact is illustrated in Figure 9). However, in this phase, the main aim was to create and validate the Framework, conceptual design and the paper prototype of the app developed based on the conceptual, theoretical and methodological considerations informed by the contextual inquiry phase. Publication **V** is directly linked to publication **IV** and presents the paper prototype of Observata app. Observata plays an instrumental role in involving users in the design and evaluation of the underlying framework and is one of the research contributions of this thesis.

The publication **IV** introduces the model that then was called a *Learning Analytics Model for Lesson observations* (Figure 10). Aware of the LA need for context-awareness (Rodríguez-Triana et al., 2015) and pedagogical grounding (Corrin et al., 2016), this model takes them into consideration while combining observed and logged interaction events.

5.2.1. Contribution 2: Model for Contextualised MMLA Classroom observations and Observata paper prototype

This subchapter presents the main contributions of this thesis – the *Model for Contextualised Classroom Observations* and the Observata paper prototype. Both have been validated in a participatory design session with practitioners and researchers (details reported below). The model is built on three main elements: *Context, data collection protocol from lesson enactment* and *MMLA data* (Figure 10).

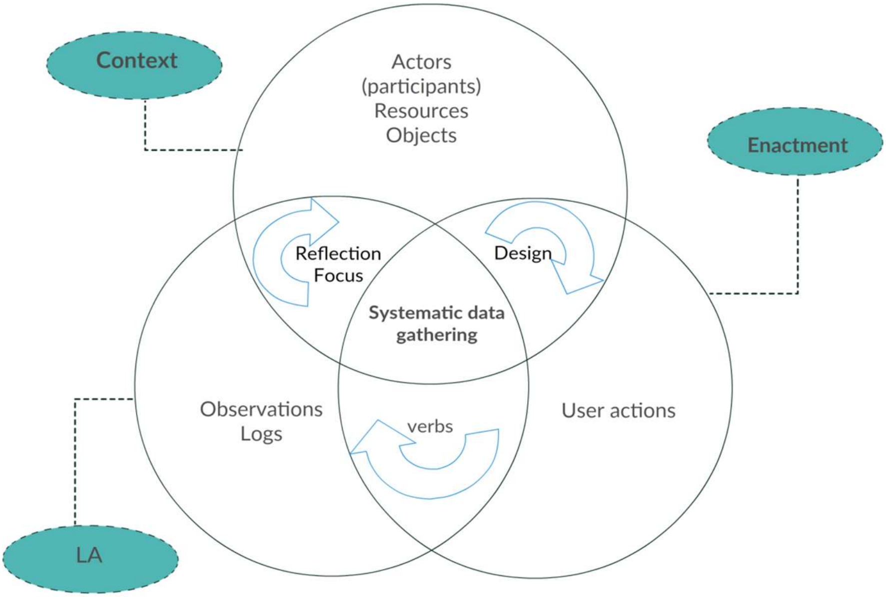


Figure 10 The Model for Contextualised MMLA Classroom Observations

Context: the model offers using contextual information to guide the data collection and analysis process (Rodríguez-Triana et al., 2015). Context and pedagogical design are reflected in the predefined LD, which is important for both – to guide the data collection or to analyse/make sense of the collected data. LD should be extracted from machine-interpretable format (this can be regarded as a part of the context) that contains information on actors, resources and objects (artefacts). Alternatively, lesson structure also can be inferred through the observed lesson structure. **Data collection from enactment:** to enable systematic data collection, codes are predefined, while systematic data from logs are automatically collected. These codes can be pedagogy or theory-driven (see Figure 10) or action-driven (or both at the same time, since several code-sets can be used for codification): since systematic data collection and codification usually entails using theory-based, validated coding schemes, this may add another layer of theoretical underpinnings (Knight & Buckingham Shum, 2017) to the data. **MMLA data:** by observing lesson enactment, the data is collected through coding learning events and aggregation of xAPI statement. Then observations and logs are put together to enable automated or semi-automated analysis.

To implement the Framework, I have also created and validated the paper prototype of the Observata app (**V**). The mock-up shows the observation view (left) with a classroom layout, subjects (actors – students and teachers) and actions (code sets), suggested xAPI generation format within context of the whole class or group activities. The scenario view (right) illustrates planned activities (part of the learning context) against real-time enactment. All the events are timestamped and visualised within the context of learning activities. Here the code-sets are derived on action-driven (behavioural) or pedagogy-driven basis.

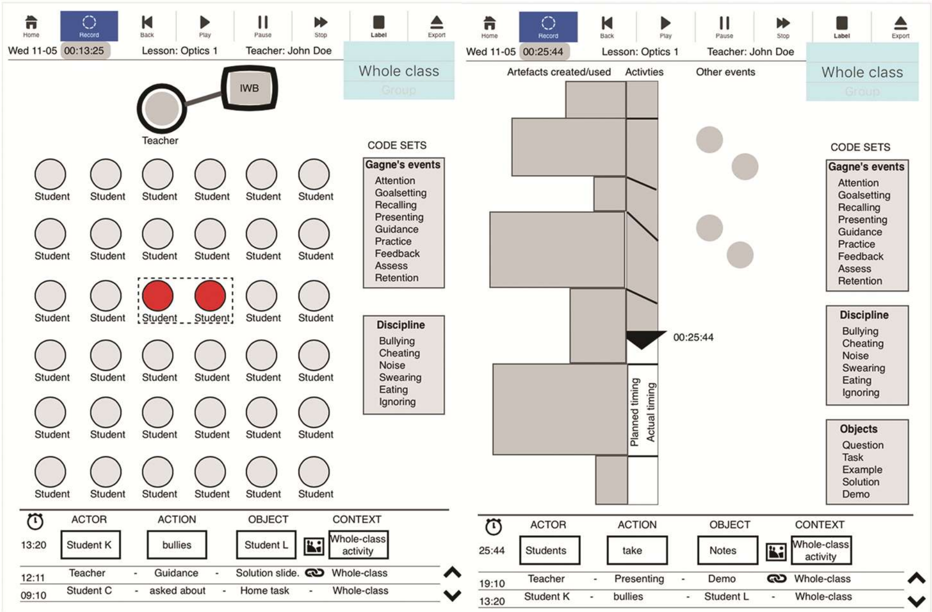


Figure 11 Paper prototype (mock-up) of Observata: classroom observation (left) and scenario (right) views of the Observata tool

Validation study: The model and the conceptual design (Figure 11) of the corresponding app have been evaluated through scenario-based research with a focus group and participatory design session with 6 in-service teachers (4 from secondary and 2 from higher education, 2 of them also being researchers). Following the scenario-based research method from the field of Human-Computer Interaction (Cooper, Reimann, Cronin, & Noessel, 2014) 5 personas based on the potential stakeholder profiles representing primary and secondary users of the application and

4 scenarios have been developed. These scenarios have used a conceptual design of a classroom observation app and the proposed model for contextualised and multimodal classroom observations (phase 1 artefact). While defining 3 main users in the previous phase (teacher, researcher and observer) – we expanded envisioned users to include 2 more (supervisor teacher and EduTech start-up head) (Table 7). These personas (users) and scenarios (use cases) were derived from Estonian semiformal requirements for classroom observations, where potentially different users are involved – novice teachers and their supervisors. At the same time, I have also relied on the wide-spread practice of blended learning practices in Estonian schools and participating stakeholders in them – such as EduTech providers, TEL researchers, teachers interested in inquiry practices. These personas and scenarios have been iteratively developed envisioning these users involved in the practice. Then, for the study, we chose 6 participants familiarized with the personas described above, having previous experience in classroom observations. One researcher moderated the design session presenting the scenarios with guiding questions after each one, used for guided interviews. The researcher also participated in the design process. The interviews were audio-recorded and coded later for thematic analysis. The artefacts have not been generated in this design session; the paper prototypes were created later by the researchers based on the specific feedback given by participants.

Table 7 Description of personas, their goals and requirements[4]

Type	Name	Goals	Requirements
Primary	Supervisor teacher	Observe and share observations	Efficiency and easiness of use
Secondary	Intern teacher	Compare the teaching execution vs intentions	Quick and effective annotations
Secondary	Edu Tech start-up head	Track the technology usage in the classroom	Ability to record activities that are using a certain tool
Secondary	Researcher teacher	Understand how pedagogical intentions are implemented (for regulation and reflection	Register, analyse, and visualize activities compare with the intentions
Secondary	TEL researcher	Automatically collect and code data with different semantics	Connect structured and consistent data with other sources

[4] Detailed personas in online appendix http://bit.ly/2skvTd2

Table 8 Overview of scenarios (use cases) discussed during the participatory design[5]

Scenario	Description	Personas involved	Process
1	A simple classroom observation case (without lePlanner	Teacher in training [Supervisor]	1. Manual context description and protocol definition 2. Classroom observation and evidence gathering 3. Observation sharing 4. Discussion
2	Observation based on LePlanner scenario	Supervisor [Teacher in training]	1. Reusing context description 2. Loading existing design 3. Protocol definition 4. Classroom observation and evidence gathering 5. Comparison visualization 6. Discussion
3	Observation of a technology-rich lesson	Head of edu-tech start-up [Researcher teacher]	1. Manual context description 2. Protocol definition 3. Classroom observations and evidence gathering with several foci of interest (several code-sets) 4. Combining two data sources 6. Research
4	Curriculum research based on the observation data	Researcher teacher [Head of edu-tech start-up]	1. Reusing context 2. Discussion and comparison of semi-automated observation transcript with hand-written annotations using video-recording 3. Data export for analysis 4. Research

Through the participatory design phase and the scenario-based research, I have defined, explored and validated the motivations for different stakeholders (reflected in the personas and scenarios), process, elements, and unit of analysis for observation data collection (reflected in the presented validated model in Figure 10). Thus, as a result of the participatory design, I validated the conceptual design of Observata, and a refined model for MMLA classroom observations. The table below summarizes the main findings and evidence of the design session (Table 9). It is worth noting that due to the participatory nature of the research design, evidence, in this case, is aggregated and not reported by stakeholder/participant groups.

[5] Scenarios http://bit.ly/2rZxDra

Table 9 Overview of the findings from the design session (RQ2)

Dimension	Findings	Aggregated qualitative evidence
Feasibility and interest	Events were perceived as a realistic and appropriate unit of analysis for observations; Predefined foci and verbs (code-sets) were interesting; Overall, the solution was regarded as interesting	Most of the participants: Stated that the predefined verbs were relevant for the easiness and consistency of data collection. Teacher (N1): *"When will this app be ready? It is exciting to wait for that minute to see real examples, how it is planned, observed and recorded"*.
Usefulness	The prototype was perceived as useful. The solution was regarded as useful as it is in line with common practice; Comparison of enacted practice with teacher intentions (learning design) using several observation transcripts was appreciated; MMLA part was regarded as the most interesting	Most of the participants: Stated that predefining the observation protocol and verbs make the approach more systematic and useful; Highlighted the importance of its use in teacher training was because observing others' lessons is the part of the teacher training. Regarded the comparison of the transcripts as a common practice, and suggested to use LA to compare the transcripts. Thought that combining observation data with MMLA datasets (data coming from a tool used in the lesson) was one of the most interesting ideas
Recommendations about the observation process	Use of several code-sets at the same time; Need for LD: documenting the time difference between the planned and the enacted practices; Inclusion of more data	Some participants: Highlighted their interest in predefining several code-sets, attending the different observation foci. Several elements of the classroom observation for students were stressed as important. Stated that there must be certain foci predefined (such as work planned, tasks, tools used, or the social level of the activities) and observed (e.g., emotions, motivation, environmental metrics etc) to connect the observations and the analysis with the learning context; Stressed the importance of reflection and comparison between the learning scenario and observation transcript; Recommended the usage of student feedback to enrich the MMLA dataset.
Instrumental recommendations	Reusing and storing protocols; Privacy issues are important; Contextualising in learning scenarios; Open coding is important; Post-editing suggested (related to limitations)	Some participants: Highlighted the need for reusing the protocols (learning scenario), storing transcripts (contextualised in learning scenario) and contextualising for later analysis. Stated that sharing the transcripts was a potential scenario;

		Recommended preserving the privacy of the transcript author (observer) and the anonymity of the participants in the learning scenario. Acknowledged the need of predefined and agreed vocabularies to ensure the interpretability of the data by other observers or LA tools, they still reinforced the importance of open coding; Suggested to revise and post-edit the transcript and to videotape the whole process to have a reliable overview of the sessions.
Limitations for adoption	A shared understanding of codes; Time constraints -difficulty to observe; Complexity of the proposal	Some participants: Underlined the importance of a shared and agreed meaning of ad-hoc added codes; Stated that due to the time constraints, it may be difficult to register observations, especially in those cases where the teachers observe; The participants raised their concern about the complexity of the proposal. Teacher (N1): *"It will require a lot of training for teachers to adopt this innovation"*.

The findings of the validation showed that the participants representing the main stakeholders – (primary: supervisor of intern teachers, secondary: intern teacher, Edutech Startup head, teacher and a researcher) have accepted the model. The model was regarded viable: through the use of Observata tool we can identify, code and combine LA-compliant observation data. Findings also demonstrated the excitement about the innovation but at the same time, indicated to the expected challenges of adoption in authentic scenarios, which can be explained by the complexity of the proposal. Another challenge is related to the availability of the LD which needs to be in a computational format and is not always straightforward. These findings informed the Phase III, contributing to the refinement of the methodological and instrumental aspects of the model. These changes offered by participants and discussed with the researchers were included in the design decisions: important suggestions from this session was the use of open coding schemas and adding qualitative data collection possibilities. Limitations related to time constraints were to be addressed, as suggested by the participants, by introducing xAPI statements post-editing function and videotaping, as well by adding photos and field notes.

The target groups for both the model and Observata are: researchers and TEL researchers, the community of teacher professional development (novice teachers, their supervisors, experienced teachers interested in the inquiry processes), and creators of TEL innovations (Edtech Startup heads or project managers). The purposes can vary across the target groups from exploratory data gathering to triangulation of multiple data sources and MMLA, from the evaluation of innovative learning scenarios to evaluation of TEL products, from teacher inquiry to the evaluation of teacher practices, LD implementation etc. The application of this model can reinforce the evidence-based educational practices, it can help TEL researchers gather MMLA data to enrich or triangulate datasets.

Summary (RQ2)

Data collection from different sources and contextualisation of LA data are important challenges in LA research. Some researchers have used the xAPI standard to connect MMLA data coming from diverse sources and LD contextualisation purposes. At the same time, observations are often used in LA studies to triangulate the findings or enrich data-sources. Informed by the previous phase of the research and the gaps identified in the literature, in this chapter, I introduced two contributions: paper prototype of the classroom observation application Observata and the *Model for Contextualised Multimodal Classroom Observations.* They have been developed through scenario-based research and participatory design. At the same time, in this phase, I have returned to the contextual inquiry phase to re-examine initial concepts in the proposal. Based on the results I have answered **RQ2**: *What are the technological and conceptual tools needed for data collection?* The *Model for the Contextualised MMLA Classroom Observations* and the corresponding app Observata can be useful and feasible tools for contextualised observational data collection. This, in its turn addresses the research problems (1.2; 2.1; 3.2; 4.1; and 4.2) and fills the gaps detected in the field: the need for mixed data from blended learning contexts can be addressed by introducing observation data in the datasets aligning two methodological paradigms; This, in its turn responds to the need of availability of interaction data from across spaces. At the same time, this is a promising approach to address the need for several data-sources and contextualisation of interaction data in authentic learning contexts. The findings show that the suggested tools coincide with users' expectations and common practice. We understood that the process was regarded as feasible and the idea interesting. The motivation and the need for such application exist and the idea was well accepted. The unit of analysis for data collection was also regarded as appropriate, realistic and feasible. However, the limitations due to time constraints and adoption-related issues due to the complexity of the proposal were also highlighted.

5.3. CONTEXTUALISED MULTIMODAL OBSERVATIONS: TOWARDS EVALUATION AND HYPOTHESIS

The last stage of the PhD covers both phases 3 and 4 (product design and software prototype *as a hypothesis)* but at the same time, comes back to phase I of contextual inquiry (publication **VI**) looking for in-depth methodological insights, further use cases and purposes. As a result, in this phase, I am covering the following research problems: the challenges such as the need for data collection from blended learning contexts; need for the alignment of methodological dichotomy of research paradigms; need for across spaces interaction data; and addressing the issues of "streetlight effect" and contextualisation of interaction data in authentic learning contexts (RP1.2; 2.1; 3.2; 4.1; and 4.2).

In this subchapter two phases of RBD are presented together: *product design (towards evaluation)* and software *prototype as a hypothesis* as an outcome of the whole research (See Figure 12). Through the research-based process, I have generated a hypothesis in the form of a software prototype. Although the model was partly evaluated through the data collected with Observata (in authentic settings), still, this phase, as Leinonen et al (Leinonen et al., 2008) suggest, is not its final stage, and goes back and forward feeding other phases. While the product (namely, Observata) was developed by an IT specialist, it should be noted that my role was to identify functional requirements, provide a conceptual design, create the personas and scenarios, analyse design session data, create paper prototype, test the product during the product development phase, report testing results and analyse the data collected with it. An overview of Observata is provided in the contributions part of this section, the details about its iterative development, previous prototypes and/or testing have not been reported here.

In this phase, along with the product design I went back to the contextual inquiry phase and took a step towards evaluation and hypothesis generation. Going back to the contextual inquiry served a purpose of establishing more rigorous methodological discourse and examine the synergy between MMLA observations and LD (contextualisation). Also, to understand the purposes and the benefits of this synergy for the researchers (one of the target groups), I have run a systematic literature review, that illustrates the methodological basis of this thesis. As this phase of the research concentrates on the data quality and contextualisation issues, the users targeted are mostly researchers and users interested in the evaluation of TEL innovations (called EduTech startup head in publication IV), thus use cases and contexts include research and evaluation of TEL projects. The questions of this phase are:

RQ3 *How can LD aid the data collection and analysis in blended learning scenarios?*(**VI***)*

RQ4 *How can CO aid the data collection and analysis in blended learning scenarios?* **(VII)**

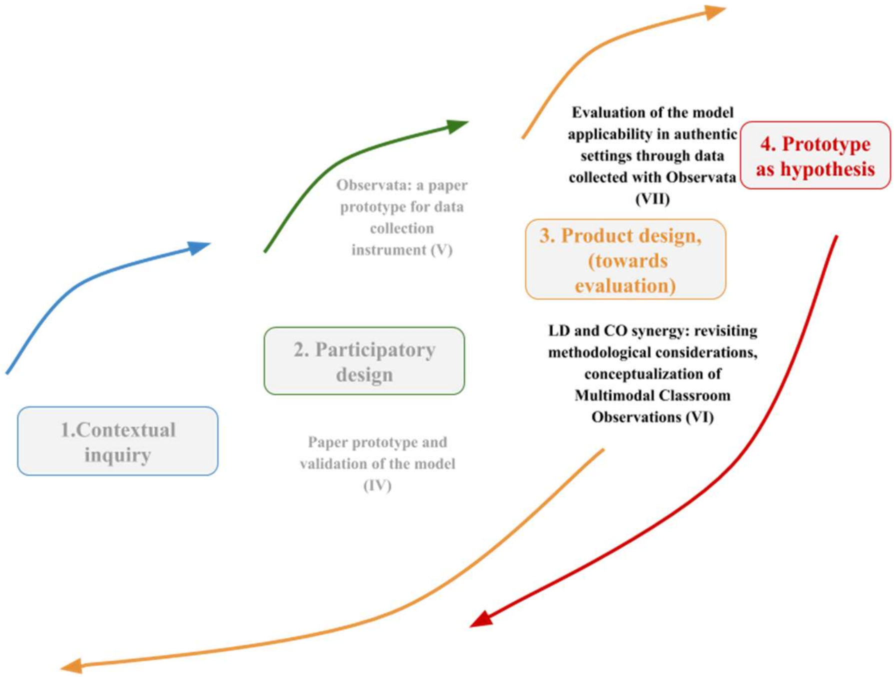


Figure 12 The last phase of research (3+1): product design and evaluation through the prototype as a hypothesis

As I have understood that connection of LD with classroom observations is not straightforward and needs more conceptualisation and methodological guidance, I decided to take a macro perspective and examine the synergy between the CO and LD, at the same time situating human-mediated and automated data collection methods from the theoretical and methodological perspective within this synergy (publication **VI)**. Main objectives were to understand the needs from educational research and methodology perspective, to overview and establish evidence basis for the synergetic relationship between the two fields, and identify challenges and open issues for connecting these two. At the same time, as the systematic synergistic connections have not been previously established in the literature, potential benefits, purposes of such research studies and user needs (from research and inquiry perspectives) needed to be re-examined.

In publication **VI**, I have done a systematic literature review following a PRISMA statement (Liberati et al., 2009). I have run a query: *("classroom observation*" OR "lesson observation*" OR "observational method*") AND ("learning design" OR "design for learning" OR "lesson plan" OR "instructional design" OR scripting*), in the databases: IEEE Xplore, Scopus, AISEL, Wiley, ACM, and ScienceDirect. Additionally, Google Scholar was added (first 100 hits).

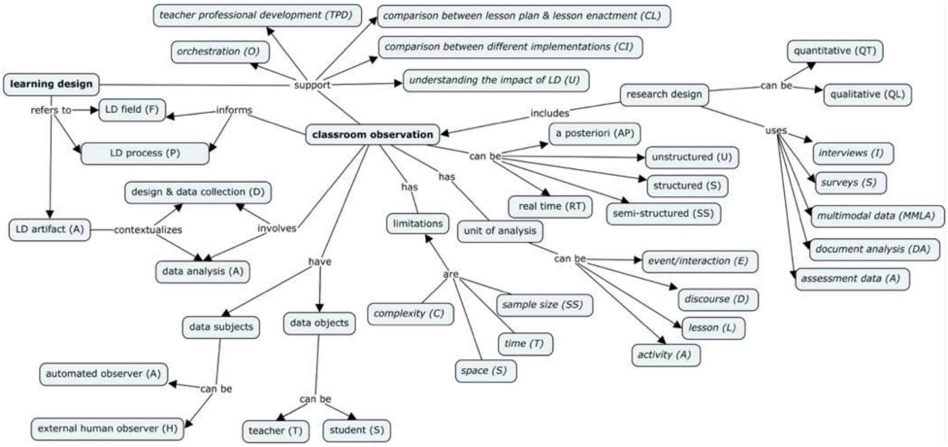


Figure 13 Illustration of LD and CO synergy based on the topics analysed[6] (RQ3)

Based on the analysis of 24 papers I have indicated that there is an added value in the alignment between these two areas, including but not limited to teacher professional development, orchestration, institutional decision-making and educational research in general. To cater to the needs for evidence-based teaching and learning practices, this review contextualised classroom observations within modern data collection approaches and practices examining the concept of *Multimodal Classroom Observations*.

The main findings of the review. There is a lack of theoretical and conceptual contributions linking LD and CO; LD as an artefact is mostly included through indirect observations (document analysis) and not though technological means; There is a synergetic relationship between CO and LD at the data gathering and analysis stage – first, LD informs CO at data gathering, analysis or both stages. And this synergy informs LD as a teaching and learning practice (design for learning); Observations can inform the LD as an *artefact* or *the process of designing for learning;* In some cases, CO can contribute to theory or the field of LD in general; The synergy can be used for classroom orchestration and teacher professional development. However, in order to make use of this synergies, there are a number of challenges identified: lack of explicit designs, lack of standards and need for conceptual and technological tools. Starting from the learning design, often this information is not explicit and formalized, therefore, in order to make use of the LDs, practitioners are requested to create them, raising the workload.

[6] In bold, central concepts of the analysis. Normal font indicates predefined codes derived deductively. In italics, emerging codes derived inductively. While using it for research, it at the same time depicts all the synergies and concept interconnections reported in the findings.

Thus, based on the systematic literature review we concluded that to enable inquiry processes, MMLA solutions could contribute to reducing the burden by inferring the lesson plan and by automatically gathering parts of the observation through automated means. Moreover, standards both in the LD and the CO solutions should be reinforced, increasing the compatibility between platforms. This strategy could contribute to the creation of technological ecosystems that support all the steps data necessary (setting up a protocol, data gathering, data analysis and sensemaking) to aid the connection between the LD and the observations. Additionally, there is a need for methodological frameworks and tools that guide the data gathering and integration, so that the learning design is taken into consideration not only to frame the data analysis (Rodríguez-Triana et al., 2015) but also to inform the observational design. However, as the literature review focused on the researcher side of LD and CO, more research and development would be needed for teacher adoption and teaching practice of this synergy. This finding is in line with challenges defined in current research on LA adoption, that include but are not limited to human factors (Buckingham Shum, Ferguson, & Martinez-Maldonaldo, 2019) and with findings on potential adoption challenges in participatory phase (publication **IV**). This systematic literature review contributed to the design of contribution 4 and the research design of the final, evaluation study.

5.3.1. Contribution 3 - Context-Aware MMLA Taxonomy

This contribution is the outcome of the PhD research and can be considered a lesson learned from previous studies. I have developed it as a result of the findings of the design session (**IV)** and systematic literature review (**VI**). Aside from the challenges identified in the beginning of this chapter regarding the need for data-sources, contextualisation, challenge of methodological dichotomies, the final publication (**VII**) research goals have been defined by TEL innovation development and adoption challenges, that include LD adoption and availability issues reported in literature (Dagnino et al., 2018)(Lockyer et al., 2013; Mangaroska & Giannakos, 2018)(Hernández-Leo, Asensio-Pérez, et al., 2018). Moreover, the complexity of the suggested innovation (Observata and the Model) for the use in authentic settings have been indicated in publication **IV** when I validated the model and the conceptual design of the app, as well as suggested in the publication **VI.** Therefore, this publication seeks the value of observations within authentic classroom settings and evaluation of the applicability of the suggested Framework based on the *Context-aware MMLA Taxonomy* (Figure 14).

The *Context-Aware MMLA* taxonomy (Figure 14) 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. 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 inferred through observations. Interoperability is ensured through identification of all actors and objects (across the learning design, logs and observations) and each event is timestamped. Once the data is aggregated in a multimodal dataset, further analysis can be executed.

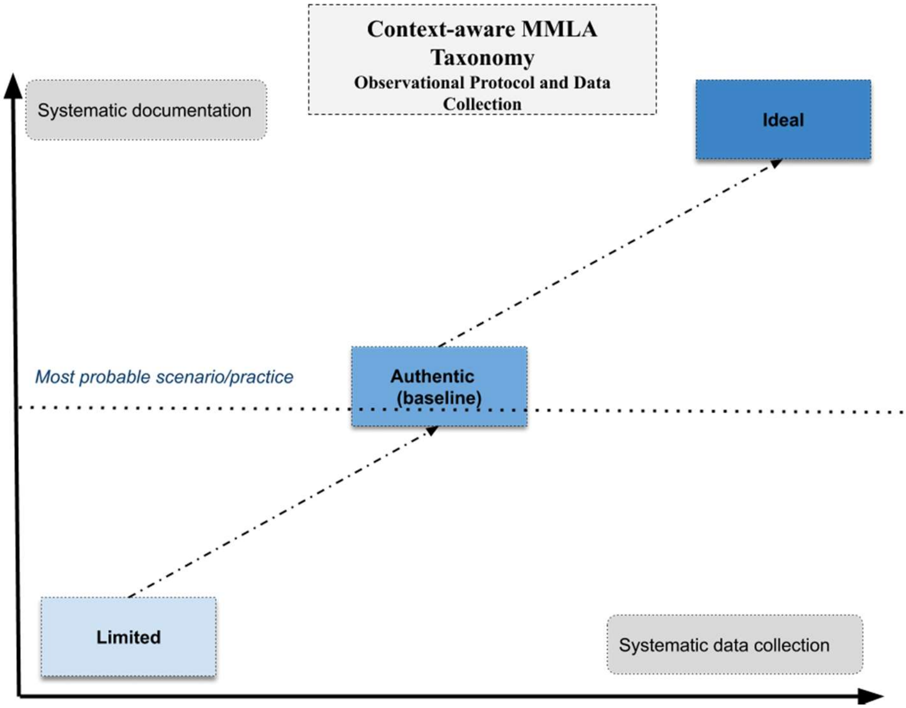


Figure 14 Context-Aware MMLA Taxonomy

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 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 systematically gathered, the lack of systematization 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.

5.3.2. Contribution 4 - Observata

Observata[7] is a research contribution of this thesis which implements my *Contextualised Multimodal Observations Framework*. This subchapter presents the app functional prototype used in the final study and describes its functionalities according to the Framework. The software prototype of Observata is presented as a hypothesis, which is not viewed as a finalized product to be tested in experimental settings.

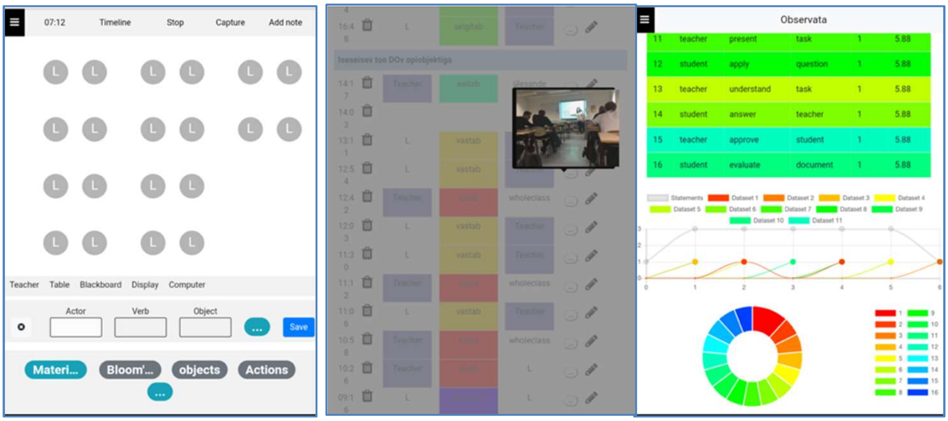


Figure 15 Observata[8] screens (from left to right): observation view to collect data in xAPI format, data visualized on the timeline, data visualized on the dashboards.

Protocol: The theoretical part of the Framework is represented by the protocols. In Observata, to initiate an observation protocol, as a first step, one should set up a lesson, to which pre-defined lesson scenario can also be attached (implemented in LePlanner scenario visualisation and sharing tool). From there, a lesson instantiation is observed based on interactions' codification. Protocols can be theory-driven (pedagogical semantics), action or behaviour-driven, as the framework supports semantically open data collection. For example, well-known taxonomy such as Blooms Taxonomy or BROMP protocol can be imported, also simultaneously, enabling application multiple theoretical constructs to the data-set (for multi-

[7] https://observata.leplanner.ee/en/

[8] Demo http://bit.ly/observata

theoretical analysis of data). Alternatively, users can create their protocols, that can be action-driven, for example, collecting simple interaction data. Aside from it, Observata supports open (inductive) coding protocols, still aggregating systematic data. Observata is meant to be semantically open and flexible with coding schemes, so I hypothesise is that it can accommodate different research agendas and questions.

Contextualisation: Regarding the LD, it is possible to register it in 2 different ways. When it's available, the LD can be imported from LePlanner. To be more precise, the following information can be imported from the LD: activities, actors, artefacts, media use etc. When it's not available, the observer can also infer the lesson plan during the enactment, by adding it through unstructured observations thus aggregating contextual information. To sum up, the app makes it possible to contextualise digital and (potentially) MMLA data within predefined LD and observed lesson structure, and it also supports the introduction of context (through theoretical constructs) based on a predefined protocol.

Data: In terms of observations, the following types are possible: structured and unstructured. The first one is modelled as xAPI statements (Figure 15, left), where actors and objects come from the LD (but can be also added later), and verbs from the protocol. The second type includes timestamped pictures and text notes (Figure 15, middle) and inferred lesson structure as a context. The data can be extracted in a .csv file for exploratory or confirmatory analysis.

Data visualisation and sense-making: The app includes a timeline of observed learning *events* contextualised within the LD demonstrating the planned against the actual enactment patterns (or inferred lesson plan in case LD is not available). Besides, it also contains a dashboard where observations can be visualised according to the xAPI elements, also in the context of the LD activities or the inferred lesson plan (Figure 15 middle and left).

Observata's conceptual design has been evaluated in the publication **V** involving 6 users in the design session which demonstrated the **protocol** and **data** dimensions of the application. In the final study (publication **VII**), deploying a multimodal dataset described above involving 2 stakeholders (project managers interested in the evaluation of TEL innovation), I have focused on the **contextualisation** and **data** dimension of the app and evaluated its contextualisation potential in authentic scenarios. The main aim of the evaluation was not the usability testing but the evaluation of the Framework.

The tool supported the stakeholders in collecting the data for a large-scale TEL project: it has been used in a digital learning resources development project (Digiõpevaramu)[9] where project managers used the tool to not only observe the classroom dynamics and understand the innovation practices (while using the resources) but also to contextualise the analysis of the digital traces. At the same time, Observata has been voluntarily adopted by additional users (Table 10): Observata is

[9] https://e-koolikott.ee

included in the CEITER[10] project LA toolkit for Estonian schools to analyse learning processes on a classroom level. The collected data is utilised for evidence-based decision making in the educational innovation process and is integrated into the EDULABS method[11]. Furthermore, Observata has been deployed as an in/pre-service teacher education tool at Tallinn University. It is planned to integrate Observata in classroom level digital innovation monitoring ecosystem, including Innolabs (project days carried out by TLU researchers).

Currently, Observata (together with LePlanner) is available in three languages: Estonian, English and Georgian. Current usage statistics for all the above-mentioned adoption processes (as of 18 November, 2019) are summarized in the table below:

Table 10 Observata usage statistics

Dimension	N
Registered users (total for LePlanner+Observata)	**991**
Number of users that initiated an observation protocol	**45**
Total observations	**339**
Total of xAPI statements	**3253**
Total of lesson protocols initiated	**267**
Total of lesson protocols with lesson scenario attached	**125**
Total of observations with learning scenarios	**187**
Average statements per observation (N=134)	**24**
Maximum number of statements per observation (N=134)	**143**
Number of observations with less than average (24) statements	**92**

Moreover, a group of researchers (University College London, UK) have adopted Observata on their own and have been using it to assist the data collection and contextualisation within LD (Fraca et al., 2019). The study analysed the physically-active mathematics classroom through classroom observations. It is worth noting, that the study involved BROMP protocol for quantitative field observations of student affect and behaviour (Ocumpaugh, 2015) that has its specific observational tool HART (Ocumpaugh et al., 2015). In an informal interview, the authors of the study have underlined the importance of flexibility in using different coding protocols (and at the same time), timestamping and defining actors using Observata as opposed to the abovementioned tool. Thus, Observata has the potential to be used for different research designs, questions and agendas.

[10] http://ceiter.tlu.ee/la-toolbox/
[11] https://edulabs.ee/opidisain-tooriistakast/

5.3.2. Final evaluation of the Framework through data collected with Observata:

Using the Taxonomy (Figure 14) of different scenarios (from limited to ideal) of data collection and analysis, I have evaluated the applicability of the Framework in authentic (baseline) settings and understanding the value of CO in data collection and analysis in blended learning. I have used exploratory research design and a case study (i.e. in non-experimental, non-confirmatory) through iterative analysis data and introduction of the other qualitative datasets to triangulate findings. In this publication I have sought to first, establish which aspects of automated observations (and MMLA in general) can benefit from human-mediated observations; second, understand what is the value of human-mediated observations for the users; and third, gather further design ideas for the development.

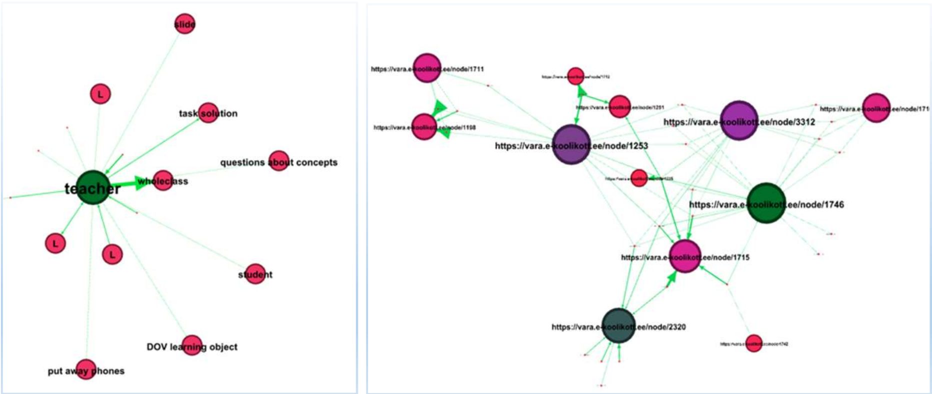


Figure 16 SNA of HMO (on the left) and AO (right)[12]

The users involved in the study were two project managers, with own research interests: in a way, it was a study within the study, where we used different data-sources, iteratively analysing them together with the stakeholders. Overall, more than 15 lessons were observed, however, I have only analysed 5 (1 lesson on two iterations) as it was enough for the purpose. The HMO was collected through Observata functional prototype (Figure 15). This data contained: systematic observations (xAPI statements), observed lesson structure (context), field notes and photos.

Aside from the observations, we used AO (logs from the interactions with digital learning resources) and teacher reflections. We followed a method for "involving the user in the loop" for MMLA solution development (Rodríguez-Triana, Prieto, Martínez-Monés, Asensio-Pérez, & Dimitriadis, 2018), we have reflected on

[12] 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)

constraints and affordances of the datasets together with the stakeholders and analysed the data iteratively (analysing, plotting and visualizing MMLA data from observations and logs (Figure 17), also applying social network analysis (SNA) techniques (Figure 16)). Interviews and questionnaires were used to collect stakeholders' feedback on two iterations. The findings of the co-design (of MMLA solution) case study show that:

1) The availability of information on different kinds of actors and artefacts physical space enriches the data from the digital one. Observations can provide with more detailed information on actor roles and their actions in the real world. In case of no LD, lessons plans can be inferred from the enactment through unstructured observations. Nevertheless, the importance of LD was still reinforced by the participants. Planned LD is an important aspect in data collection and analysis, but complementing it with unplanned, implicit design decisions through observer inferred patterns can further contextualise the data analysis.

2) Apart from the lesson plan, theoretical constructs such as pedagogy (i.e. Blooms Taxonomy) and behaviour can be introduced through the structured codification of observable learning events for richer data analysis. This can aid theory-based, confirmatory analysis.

3) Both, human-mediated and automated observations bring complementary information to the datasets: according to participants, the aim of alignment may not be a complete integration, as these two datasets may represent two different realms and semantics, 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, and the data available, the alignment between semantics may or may not be needed.

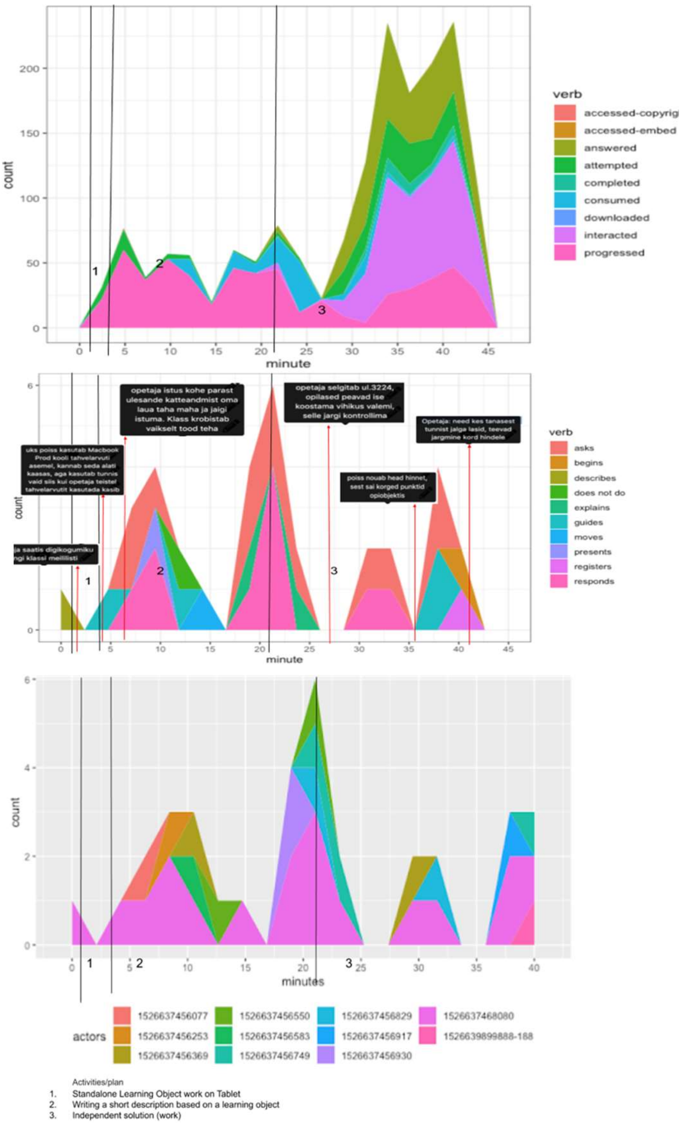


Figure 17 Examples of analysis and visualisations[13]

[13] On top - interactions in digital space, in the middle - interactions from physical space with field notes and logs. In the bottom - the number of observed actions per actor, the teacher is dark pink) contextualised in observed lesson structure. Black boxes on the plot mainly describe additional information as noted by the observer ie, last comment reads: teacher announces that who left earlier will be graded after. Normally, in Observata this is visualised on the timeline, timestamped. Link to the analysis and questions http://bit.ly/MMLA5moresso

According to the participants, systematic (or structured) observations allow for quantitative analysis of data while still offering rich context derived through non-automated means. This aspect is an important finding since the context can mitigate the lack of LD, that sometimes not available due to e.g. technical or adoption challenges as reported by the previous research. This claim is also supported by the fact that when presented with two types of data analysis (SNA and plotted interaction metrics) from two data-sets, the stakeholders did not see the benefit in SNA analysis, as it did not support the contextualisation of the AO (Figure 16). Other qualitative data sources such as teacher reflections can provide with increased contextual information in MMLA where this context is missing: qualitative data enable validation and triangulation of the data gathered through automated means and contextualises them. Overall, balance is needed between user needs (i.e. contextualisation for analysis and sensemaking) and data affordances. Depending on these needs, data can be further structured - for instance, field notes and photos can be coded later and timestamped). Other qualitative data sources can be further introduced to enrich the available evidence, validate/triangulate findings or contextualise the data analysis. The part of this qualitative evidence from the finding is reported below (Table 11). Full evidence is reported in the publication (**VI**).

Table 11 Part of the findings of the final study (RQ4)

Findings	**Qualitative evidence (2 respondents, 2 iterations)**
It is possible to extract knowledge from two data-sets (classroom observations and digital logs)	<u>Patterns of usage by using two-datasets:</u> *"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	<u>Extracting knowledge only based on one data-source</u> *"No, certainly not", "No, definitely no", "There is definitely an added value here."* <u>Two data sets complementing each other:</u> *"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"*
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. Evidentiates implicit and explicit LDs**	<u>Contextualisation and analysis</u> <u>Observer-inferred learning activities:</u> 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"* <u>Predefined LD and observed lesson structure:</u> *"gives 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*

by providing two layers of contextual information – predefined LD and observed lesson structure. **2. Coded (inter)actions themselves explain digital interactions.** **3. Theoretical concept and constructs - bring another layer of context.**	*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 (structured 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"*.
Two datasets bring different semantics from different realms and dimensions	Data integration and semantics: *"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"*.

Each level of the taxonomy can be used for different types of research designs i.e. the use of highly structured observations based on predefined coding can contribute to confirmatory research and creation of hypothesis space through labelling of learning constructs within MMLA (Di Mitri et al., 2018). Overall, based on the feedback of the users ideal, authentic or limited scenarios of data collection and analysis the benefit of contextualisation of data analysis and sense-making is evident. However, an ideal case would require structured data gathering that can contribute to three-level contextualisation of data through *predefined design, observed lesson structure, and structured observations* (Figure 18).

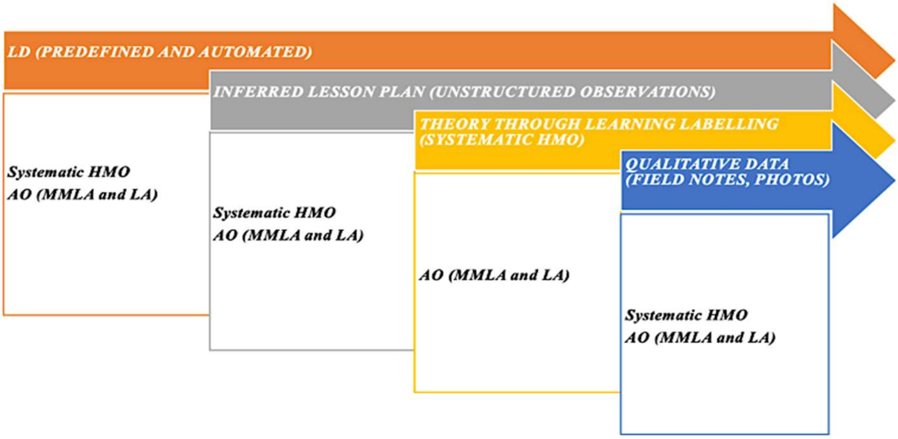


Figure 18 Layered contextualisation levels supported by the Framework and afforded by Observata

Additionally, according to the participants, sense-making can be further supported by the introduction of multimodal dashboards where even qualitative information can be timestamped and visualized (using filters). Overall, in line with previous research, our findings indicate to the importance of guided data collection and analysis (Rodríguez-Triana et al., 2015) and LD and/or theory-driven contextualisation of LA data (Gašević, Dawson, & Siemens, 2014) on different levels.

Participants also reported that due to the compliance data privacy regulations considerations, the providers of educational technologies need to anonymise digital traces by default. This design issue introduces an extra level of complexity, especially in authentic scenarios, since it is not possible to identify users across datasets, which is essential for MMLA purposes.

Summary (RQ3, RQ4)

This chapter has answered to the RQs informed by the research challenges identified in the literature: the need for data collection from blended learning contexts; the need for the alignment of methodological dichotomy of research paradigms; the need for across-spaces interaction data, and issues of enrichment of LA data-sources and contextualisation of interaction data in authentic learning contexts have created the basis for this chapter. At the same time, evaluated the main contributions of this thesis. *Framework for Contextualised MMLA Observations* applicability in authentic settings through classroom observation app Observata and introduced another contribution - *Context-Aware MMLA Taxonomy.* Finally, I have delivered the main hypothesis of this thesis in the form of software prototype Observata.

More concretely, in this last research phase, I have taken a macroscopic look into the question of LD-driven data collection and analysis answering the following questions: **RQ3** *How can LD aid the data collection and analysis in blended learning scenarios?* According to the findings, there is a synergetic relationship between CO and LD at data gathering and analysis stage by LD informing CO at data gathering, analysis or both stages. This synergy informs LD as well as teaching and learning practice (design for learning) and can support teacher professional development and orchestration. There is a lack of conceptual and technological infrastructure and tools to connect these two related fields which this thesis is targeting.

RQ4 *How can CO aid the data collection and analysis in blended learning scenarios*? Classroom observations can contextualise LA data on several levels (Figure 17). In the authentic scenarios, HMO can contextualise data analysis and sense-making, where due to adoption or technological challenges LD is not available. Also, to enable the contextualisation of data for sensemaking at three levels, predefined LD is needed; these three levels of contextualisation include: contextualisation of AO (MMLA and LA) and HMO within LD, contextualisation of AO (MMLA and LA) and HMO within LD and/or inferred lesson structure, contextualisation of AO within structured observations. An additional layer of contextualisation can be supported by other qualitative data, which, while is supported by Observata, goes beyond the scope of this thesis contributions and claims.

5.3.3. Summary of findings

RQ1 *What are conceptual, technological, methodological considerations and unit of analysis for pedagogically grounded and theory-driven data collection and analysis of across-spaces interaction data?* (**I, II, III***)*

To respond to the first question, in the contextual inquiry phase, through literature review and establishment of existing challenges in the field, exploratory case study (with 12 lessons observed involving 2 coders) and proof of concept I have developed requirements and the methodological considerations and the mental prototype (conceptual design) of the app Observata. At a conceptual level, coupling *Uptake Framework*, the event as a unit of analysis and xAPI standard, it is possible to collect LA-compatible HMO. It proved feasible to accomplish this on a technological level but specific tool development became necessary. Based on the results of the literature review and exploratory study I have defined the methodological considerations and observational protocol, that in its turn informed the development of specific conceptual and technological tools in the second phase of the research.

RQ2 *What are the technological and conceptual tools needed for context-aware MMLA observational data collection?* (**IV, V**)

This question was answered by the phase II, where I have designed the Model and the conceptual design of the app Observata through the development of personas and scenarios and participatory design session. To answer this question, took a step towards understanding the process, elements, and motivation of data collection for different stakeholders. Because of this, the Model was validated in the participatory session (involving 6 different stakeholders/personas) and accepted by participants. Observata design ideas were further refined and revisited and resulted in the paper prototype that became the basis for the product development phase. The findings showed that the need for mixed data from blended learning contexts can be addressed by introducing observation data in the datasets aligning two methodological paradigms; this, in response to the need for data collection from across-spaces interactions. At the same time, it is a promising approach to address the need for several data-sources and contextualisation of MMLA interaction data in authentic learning contexts. The findings also demonstrate that the suggested tools coincide with users' expectations and common practice.

RQ3 *How can LD aid the data collection and analysis in blended learning scenarios?* **(VI)**

Overall, the main conclusions of the research have been drawn based on the last phase of the research, which reflects on the phases III and IV of RBD. At the same time, I went back to the contextual and participatory design phases. After the development of the functional prototype, through a literature review, I revisited the synergetic relationship between MMLA Observations and LD. According to this review, there is a synergetic relationship between CO and LD at data gathering and analysis stage by LD informing CO at data gathering, analysis or both stages. This synergy informs LD as well as teaching and learning practice (design for learning) and can support teacher professional development and orchestration. Although, it is worth noting, that for this PhD the benefits of this synergy are unidirectional i.e., reflects on how CO can benefit from LD. However, the introduction of LD due to different technological or adoption issues makes it difficult to adopt such contextualisation effort widely.

RQ4 *How can CO aid the data collection and analysis in blended learning scenarios*? **(VII)**

I also sought to evaluate the applicability of the Framework in authentic settings through the development of *Context-Aware MMLA taxonomy* (see Figure 14*)* in a co-design case study and to understand the value of Observations within MMLA with the data collected with the software prototype. Based on the results of the co-design case study participants thought that:

1. *In authentic scenarios*: HMO can contextualise data analysis and sense-making, where due to adoption or technological challenges LD is not available. Qualitative data such as teacher reflections, field notes etc., create an additional layer of contextual information, some of it can be gathered through Observata. This reinforces the need for a qualitative dimension of data sources.

2. *In ideal scenarios* (see Figure 14) use of HMO can further enhance contextual information, where it is technically possible (actors are identified and cross-referenced across spaces, LD is provided). Several layers of contextual information make it possible to have context from: first, predefined LD, second - observed lesson structure, and the third - systematic

observations. Thus, we can contextualise the data in a layered manner: AO (MMLA and LA) and HMO within LD, AO (MMLA and LA) and HMO within LD and/or inferred lesson structure, AO within structured observations. According to participants views, these contextualisations can happen with the support of Observata. An additional layer of contextualisation can be supported by other qualitative data, which, while is supported by Observata, goes beyond the scope of this thesis contributions and claims, can be still collected qualitatively (photos or fieldnotes) and can be structured later on using Observata post-editing feature of learning events.

3. *In all the scenarios,* both, HMO and AO complement each other through different taxonomies and semantics, HMO provides contextual information for data analysis and can introduce theoretical (learning) constructs in the data sets, which is an important factor for data-analysis and sensemaking.
    a. Due to data analysis and sense-making considerations, the use of systematic observations is reinforced, so data can be gathered in qualitative form and later coded, or recoded to increase reliability.
    b. Multimodal Dashboards are to be developed in a way that they further contribute to data analysis and sensemaking, provided that the inclusion of qualitative data-sources is also important.

Finally, all these findings will inform future research directions and development needs (reported in a separate section (6.3).

5.4. RESEARCH VALIDITY, RELIABILITY AND LIMITATIONS

This research has not been straightforward and confirmatory. It has been mostly messy and exploratory by nature. The entirety of the research rigour is tied to the meaning-making and negotiation of the researchers and practitioners (stakeholders) views. Because of the inherent complexity of the main objective of the research, and the research-based development of the main contribution—*The Framework for Contextualised Multimodal Observations*, the rigour of the research and objectivity of the knowledge lies between the researcher and participant views. This is also justified by the chosen methodology of RBD. As reported in the methodology chapter this research is a hypothesis-generating study. Therefore, it has been exploratory and most of the findings are design or conceptual artefacts generated through qualitative research. In qualitative research, the concept of validity is different from quantitative research validity (Cohen et al., 2018); As reliability and validity is an inherently quantitative research concept brought from positivist approaches, in qualitative settings the most important factor is the naturalistic approach (Golafshani, 2003). As a researcher needs to establish both, the validity and reliability of research within the research paradigm used (Cohen et al., 2018; Golafshani, 2003), in DBR (and in RBD, as its adaptation), the resulting principles are perceived as having greater external validity than those developed in laboratory settings (Wang & Hannafin, 2004). Thus, in my PhD, the chosen methodology ensures the external validity of the research. As for the internal validity, in qualitative studies it lies is in the rigorous, truthful description of the research procedures and extensive data interpretation from different angles (Cohen et al., 2018). This research has truthfully and rigorously described all the steps, processes and procedures in the data collection or analysis (publications **II**, **IV**, **VI** and **VII**).

Limitations of this research are mainly related to the sampling methods (often convenience sampling was used) and the size of the sample. The actual design session with all the envisioned personas (stakeholders) was scheduled only once and the evaluation phase involved a relatively small number of participants. In the last phase, the evaluation of the Framework applicability happened in an authentic setting, involving only one persona (represented by 2 stakeholders) out of envisioned 5 personas. This is also justified by the complexity of the suggested contribution but also the used methodology, that on one hand, at this point, could not be evaluated with all the envisioned personas defined in the participatory phase and on the other, due to the need for evaluation in authentic settings. At the same time, according to the chosen methodology, the final output of the research – the Framework and the corresponding app are not a finished product but a prototype. Since the final study aimed to seek the value and evaluate the quality of the data, all the stakeholders would not be in the position to evaluate its design or value in authentic settings. While the users were progressively involved in the design, enactment and evaluation as suggested by (Rodríguez-Triana et al., 2018), those evaluations where gradual across iterations by actively involving a total number of 10 participants.

In summary, most of the findings of this research are not generalizable to other cases, and the hypothesis generated through the RBD approach is yet to be tested and evaluated through further iterations and in different use cases. The issues and future research lines that are to be addressed are detailed in the chapter overviewing future research.

6. CONCLUSIONS AND FUTURE WORK

Context of the body of research (theoretical background, challenges in current research and gaps) defined conceptual and technological landscape, as well as research agenda and methodological considerations for my PhD. The main objective of this thesis was to *Align of Human-Mediated (HMO) and Automated Classroom (AO) observations and Learning Design (LD) to enrich the data-sources and contextualise the data analysis in blended learning.* To achieve this objective and connect human-mediated and automated observations and contextualise data analysis, I have used RBD methodology with different data collection and analysis methods in each study. Overall, I have carried out 4 studies (1 systematic literature review, 2 case studies and 1 scenario-based design session with focus group interviews involving overall 10 participants and observing over 17 lessons) and 2 theoretical proofs of concept.

I have developed 4 contributions through RBD process – *the model and the protocol for MMLA observational process,* the *Model for Contextualised MMLA Observations*, designed classroom observation app Observata and created *Context-aware MMLA Taxonomy* that classifies different data collection protocols. In line with RBD, I have followed four phases, iteratively going back and forth through these stages. Iterating from contextual inquiry to the design and research phases, both, researchers and participants take part in the meaning-making and development of innovation. At the end of the research, a hypothesis is generated in the form of *a Framework* and corresponding classroom observation application. The main hypothesis is that with the *Framework for Contextualised MMLA Observations,* instrumentalised through the classroom observation app Observata, it is possible to *align HMO and AO and LD to enrich the data-sources and contextualise the data analysis in blended learning* using different protocols and levels of documentation as defined by *the Contextualised MMLA Taxonomy.*

As defined in the publications section of this thesis, this research has resulted in 7 publications (3 conferences papers, 1 demo paper and 3 journal articles (1 forthcoming, in print). The main findings of the research are summarized below:

- The need for mixed data from blended learning contexts can be mitigated by aligning two methodological paradigms through the observation of across spaces interactions (AO and HMO);
- We can use the *event* as a unit of analysis to collect across-spaces interaction data both for AO and HMO;
- HMO-based aggregation of xAPI statements from physical settings can be used to align the data coming from two spaces;
- There is a synergetic relationship between CO and LD at data gathering and analysis stage by LD informing CO at data gathering, analysis or both stages;

- Alignment of LD with HMO and AO enables layered contextualisation;
- HMO can contextualise data analysis and sense-making in authentic settings, where due to adoption or technological challenges LD is not available;
- HMO can introduce theoretical constructs (learning and not only) in the MMLA data-sets.

6.1. THEORETICAL IMPLICATIONS

Following the overarching methodology chosen for the thesis, this work has presented the main, overarching contribution - the *Framework for Contextualised MMLA Observations* consisting of 3 smaller contributions: *the model and the protocol for MMLA observational process,* the *Model for Contextualised MMLA Observations*, *Context-aware MMLA taxonomy;* and Observata, that illustrates and implements the framework. While practical implications are detailed in chapter 6.2 for each envisioned persona (user), we foresee that the theoretical implications of this thesis will mostly benefit research community, by answering the challenges and delivering solutions for the gaps indicated at the beginning of the thesis.

The TEL community can make use of the MMLA observation protocol and the Framework to respond to the need for **mixed data sources** for the analysis of teaching and learning processes (RP1.1) and overcome the challenge of gathering evidence from **blended learning context** (RP1.2.). This can happen by **aligning two research paradigms of LA and CO** (RP2.1) with the **interaction data from two spaces** through AO and HMO (RP3.1). In its turn, it would require tackling methodological challenges, such as the definition of the **unit of analysis and technological infrastructure** (RP3.2). For the abovementioned research problems, I have suggested using similar standards across spaces (xAPI), have conceptualised and defined the event as the unit of analysis, created a model and MMLA observation protocol, systematisation and alignment of the HMO and AO data (contribution 1) and offered solutions for MMLA data collection and contextualisation in authentic settings. At the same time, I have presented solutions to the challenges of **"street light" effect present in LA** and **data contextualisation** (RP 4.2) through the contextualisation of HMO and AO on several levels within LD, inferred lesson plan or AO within HMO (contributions 2,4), using Observata for data collection as a technological solution (contribution 4). All of this can happen in different learning contexts and scenarios, but most importantly, in authentic learning settings, as defined in *Context-Aware MMLA taxonomy (*contribution 3). Initial evidence shows the potential of suggested contributions for **LA and LD research communities** interested in synergies between the LD and LA, and provides specific methodological, theoretical and technological solutions for data contextualisation; **MMLA community** with new prospective, and specific theoretical and technological solutions towards systematic inclusion of HMO data in MMLA datasets, also the contextualisation and sense-making of MMLA data analysis. At the same time, provides the guidance for reflection on the existing evidence, its limitations and potential in authentic scenarios. Besides the research problems defined beforehand, these contributions could also be a solution for the **MMLA community** towards a systematic protocol to guide the design, collection, analysis and validation of the data; **Observation methods research** community could adopt the novel methodological, theoretical and technological solutions towards integration of AO in HMO; The communities of **teacher professional development** and **teacher inquiry** could potentially use the conceptual and technological instruments developed in this thesis.

Furthermore, the technological and conceptual contributions presented in this thesis can be further appropriated, adopted and/or developed by third parties for their own research and practice needs, without the involvement the author of this thesis.

6.2. PRACTICAL IMPLICATIONS

As this PhD thesis took a pragmatic approach, balancing the design and research needs, the problems detected in the research community and the needs of practitioners informed the design artefacts that had been gradually evaluated in different phases with 10 users representing or familiarized with the practices and personas detailed below (Table 12). Additional 45 users (based on voluntary adoption) have initiated 339 observations in Observata (Table 10). Based on the evidence and lessons learned during this research, Table 12 compiles the implications and benefits that the contributions from this PhD (may) have for the different personas addressed in this work, namely: supervisor teachers, intern teachers, Edu Tech start-up heads, researcher teachers, TEL researchers, each having their aims. The table below presents the overall contribution – The *Framework for Contextualised MMLA Observations* in 4 contributions and is categorized by specific use cases (scenarios) and benefits for main personas (stakeholders) they may have.

Table 12 Main personas, scenarios and potential benefits of the contributions of the thesis

Personas involved	Scenario	Added value of the contributions (**O** - Observata, **MC** – methodological considerations, **M** – model, **T**- taxonomy)
Intern teacher, supervisor	A simple classroom observation case (without pre-defined context)	**O:** Supporting the collection of observation data for the reflection on teaching practice; Sharing observations; Visualising systematic observations
Supervisor, intern teacher	Observation based on a predefined LD	**O:** Supporting the collection of data for the understanding of LD implementation and reflection on teaching practice; Observing and sharing observations; Visualising systematic observations.
Edu-tech start-up heads, researcher teacher	Observation of a technology-rich lesson	**MC:** Providing the protocol for tracking the TEL use in the classroom; **O**: Collecting xAPI compliant systematic data with human observations; Contextualising of the observations within LD; Visualising systematic observations
Researcher teacher, head of Edu-tech start-up	Curriculum research based on the observation data	**O:** Supporting the collection of data for (teacher) inquiry involving observations; Contextualising observations within LD
TEL researcher	Gathering MMLA observations for research, evaluation of designs (tools and interventions)	**MC:** (Methodologically) guiding MMLA data collection, analysis and contextualisation **M:** Helping researchers reflect on the different dimensions that may influence MMLA observations in a classroom **O:** Gathering xAPI compliant systematic HMO; Contextualising observations within LD **T:** Helping researchers reflect on the existing evidence, its limitations and potential in authentic scenarios

6.3. FUTURE WORK

The product design phase resulting in a hypothesis needs to be revisited and tested in authentic settings. At the same time, more participatory design sessions are needed for further versions of the software. Nevertheless, the software is still used in several contexts by the most of the personas defined in the publications (**IV** and **VII**) – this includes mainly TEL researchers, novice and supervisor teachers (pre-service teacher education), researcher teachers (expert teachers for inquiry). While we do not have data on it being used exactly by Ed Tech start-up heads, this persona can be represented by the TEL project managers, as it was used in a large-scale TEL project evaluating the impact of the development of innovative digital learning resources (described in the chapter 5.3.3). As defined in the *Context-Aware MMLA taxonomy*, in order 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: Observata will need to be further developed according to the findings of the final co-design study. In addition, aspects such as data reliability and validity as well as data privacy issues should be solved in future both at the technological and methodological level by integrating inter-rater reliability solutions. As for data privacy issues, this also has to be addressed by consent forms or data anonymisation.

The Framework and the application would need to be further tested with all the envisioned personas (stakeholders) and other contexts, including the ideal scenario context (see Figure 14 *Context-aware MMLA Taxonomy*). Also, in accordance with the findings of the final article (**VII**), several other aspects such as innovation adoption challenges, technological development and further conceptual development of the Framework further work needs to be done.

This research has also opened future lines of research:

- This PhD thesis draws from previous theoretical works proposing the alignment between LD and LA, and not only adds evidence about the synergies between both fields but also enriches the scope of the synergies by bringing in the field of observations, which has traditionally run in parallel. Thus, a different domain could benefit in the future from further analysis of relations between LD-CO, LA-CO, and obviously LD - (MM)LA-CO. In terms of approach, this thesis illustrates the unidirectional synergy between LD and CO(LD-CO). Thus, future research could benefit from exploring the synergies between LD-CO bidirectionally so that both LD and CO practices can enrich each other. To achieve that goal, it will be necessary to develop and evaluate conceptual and technological solutions that support LD and CO processes.
- At the technological level, Observata enables the generation of xAPI statements compatible with other digital traces (as illustrated in Publication **VII**). However, to facilitate the adoption of MMLA in the context of classroom observations by final users, it would be necessary to integrate MMLA data and visualize it on a dashboard. On this regard, the on-going MMLA efforts to support this kind of solutions, both, at Tallinn University (Shankar et al., 2019) and abroad (Schneider, Di Mitri, Limbu, & Drachsler, 2018), look promising.
- At the methodological level, the MMLA community often lacks systematic protocols to guide the design, collection, analysis and validation of the data. To solve this problem, in the future, the CO community could contribute with their expertise in these matters (Bakeman & Gottman, 1997), providing guidelines for MMLA as we started envisioning in Publication **VII.**

- In terms of learning contexts, there is a current interest for analysing co-located collaboration across spaces both at TLU (Chejara, Prieto, Ruiz-Calleja, Rodríguez-Triana, & Shankar, 2019; Kasepalu, R., Pablo, L., Santos, P., & Ley, 2019) and in other EU institutions (Praharaj, Scheffel, Drachsler, & Specht, 2018). In these contexts, Observata would be of great help in collecting interaction data from the physical space ready to be used in their MMLA studies. In fact, Observata's data could contribute to the creation of the "ground truth" necessary in their studies to validate the data collected through the digital traces.
- Also, Observata could be used to support teacher professional development, e.g., for teacher inquiry, for instance, in the following cases (Saar, M.; Prieto, L.P.; Rodríguez-Triana, M.J.; Kusmin, 2018) (Hansen et al., 2013) or in a more institutional manner to understand teacher practices. This adoption could be supported by integrating Observata in pre-service and in-service training programs.

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Analyzing Learning Flows in Digital Learning Ecosystems

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Abstract. This paper envisages emerging trends and methods in learning analytics for post-LMS era, where learning increasingly takes place in distributed, user-defined digital learning ecosystems. Inspired by the recent developments on uptake framework and Experience API, we propose learning flow as the main unit of analysis while studying learning-related interactions.

1 Introduction

Recent changes in online learning environments towards openness and distribution, and the paradigm shift towards learner-centered approach have brought out the need to better understand how learning takes place in such systems. We conceptualize new e-learning systems as dynamic and evolving Digital Learning Ecosystems (DLE) and assume that DLEs may be governed by ecological principles [1]. Knowing empirically which ecological principles are applicable to DLEs, and how they function, would enable designing new type of learning interactions in DLE and managing these as learning environments. But in order to take an in-depth look at how a DLE functions and which ecological principles appear in these systems, new approaches for learning analytics are required. While traditional approaches in educational data mining and learning analytics are based on analyzing frequencies of events (e.g. page views, posts, comments), Suthers et al. [2] have argued that exploratory sequential data analysis of learners' digital footprints might provide better insight to individual and collaborative learning processes. In this paper, we are going to explain why the next generation TEL systems, should contain such new kind of learning analytics tools that support learning interactions based on ecological principles.

Previous research on Technology-Enhanced Learning (TEL) has regarded learning interactions as an important unit of analysis, which has been studied at various perspectives [3–5]. Most of the TEL research is based on the data collected through learner-reported surveys [6, 7], educational data mining techniques [8, 9], qualitative text analysis [10] or social network analysis [11]. We argue that each of the approaches alone is neither sufficient nor relevant for researchers aiming at conducting large-scale learning analytics in Digital Learning Ecosystems (DLE). This paper envisages emerging trends and methods in learning analytics for post-LMS era, where learning

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increasingly takes place in distributed, user-defined digital learning ecosystems. Inspired by Uptake Framework by Suthers and Rosen [2] and recent developments towards Experience API [12], we propose to use learning flow as the main unit for learner interaction analysis.

2 Digital Learning Ecosystems

We define DLE as '*an adaptive socio-technical system consisting of mutually interacting digital species (tools, services, content used in learning process) and communities of users (learners, facilitators, experts) together with their social, economical and cultural environment*' [1]. DLE consists of a large and distributed set of dynamically evolving online tools and services, which are selected and used by different groups of learners and facilitators. DLE is a third-generation virtual learning environment, replacing traditional Learning Management Systems in coming decade.

While the second generation of TEL systems presented software systems as an environment where learners and teachers interacted with each other as well as with learning resources, we propose to turn the roles upside down for DLE. In DLE, the "species" or "organisms" are various interacting software tools and services together with their users, while larger technological landscape, social and cultural contexts play the role of the "environment". This is a change of paradigm, which will help us better understand, analyze and design the future tools and services to enhance learning. We are not using ecological concepts as metaphors; we propose to extend the ecosystems theory towards the digital world.

The three main principles of ecology may be translated into DLEs as following:

The first principle in ecology is that the flow of energy and the exchange of matter through open ecosystem is regulated by the interactions of species and the abiotic component (by the web of energy and matter). Reyna [13] conceptualized "teaching and learning" as this energy that empowers digital learning ecosystems to changing "information to knowledge". The permeability of a DLE to the export and/or import of information and knowledge depend on the nature of the 'architecture' of the components of the system (e.g. connectivity, clustering), the characteristics of species, and their diversity and distribution, and interactions between them (such as commensalism).

The second important ecological principle is existence of the feedback loop to and from the environment that enables species to be adaptive to the environment and the environment to change as a result of species. A recent literature in evolutionary theory elaborates the notion of niche construction [14] as an ecological factor that enables organisms to contribute for and benefit from environmental information. If organisms evolve in response to selection pressures modified by themselves and their ancestors, there is feedback in the system. In our approach to DLEs, the "service-species" are activated by users with different roles (learner, facilitator) and their learning intentions. Ecological psychology [15] suggests that learner's/teachers' direct perception of the learning environment's action potentialities (or so-called affordances) varies and this would give the variability to the actual use of services in the e-learning system. The niches for each service-species in the digital ecosystem may be collected from this user-behavior, for example by learning analytics.

The third important principle that we extend from ecology to DLEs is associated with the communicative interactions between species. The digital community is a naturally occurring group of "service-species" populations in e-learning ecosystem who inhabit the same habitat (but use different niches) and form temporary coalitions (communities). For example the mutualisms such as parasitism, symbiosis or commensalism may appear between service species are associated with sharing the re-sources and associate with our first principle (energy and matter exchanges in the network). Other type of interactions, based on communication, which assumes mutual awareness, signaling between agents (or using the accumulated signals left into the environment) may be distinguished as well.

We assume that as a result of applying these three ecological principles on designing the next-generation online learning platforms, an open, loosely coupled, self-organised and emergent DLE can evolve. Yet, this is a hypothesis that should be empirically validated by using new approaches to learning analytics in DLEs.

3 Defining Interaction

Interaction is a concept that is common to the systems in nature as well as to human-technology systems. Wagner defines interaction as '*reciprocal events that re-quire at least two objects and two actions. Interactions occur when these objects and events mutually influence each other*' [16]. In natural systems we may differentiate between resource-based interactions between different agents of the systems that generate transformative flows across chains of resource networks, as well as communicative interactions between agents. Suthers et al. [2] distinguish between educational "inter-action" including direct encounters and exchanges with others and "interaction" based on indirect associations via persistent artifacts - both lead to individual and group-level learning. Based on some interactions in educational systems the meaningful uptakes appear during interaction of learners, teachers and resources when information is transformed to knowledge. In larger scale interactions in DLE generate learning flows and patterns within DLEs, which may be used for facilitating learning. In our learning analytics framework these learning flows are crucial.

We look at the concept of interaction from the following aspects:

(a) What actors interact in DLEs and how they appear to be mutually connected? What is characteristic to educational interaction in DLEs?
(b) What interactions/patterns of contingencies appear in DLEs?
(c) What kind of uptakes appear as a result of interaction in DLEs?

Distance education theorists have broken the interaction concept down to mainly based on the roles of the human and inanimate actors [17]. Moore's theory of Three Types of Interaction includes learner-content, learner-instructor, learner-content and is the first systematic approach to defining the typologies of interactions in distance education. Within the learning communities different types of interactions are crucial for the learning [3, 18]. Anderson has expanded Moore's three dyads of interaction - learner-content, learner-teacher and learner-learner to include content-teacher, content-content and teacher-teacher interactions [3]. Anderson's model is learning-centered and also takes into account material resources. For analytical purposes in DLEs we have to consider mainly those interaction actors and interaction dyads that can be automatically traced.

In education didactic interactions have several particularities – they happen be-tween actors with different level of knowledge and competences. Moore's Theory of Transactional distance [18] – describes the psychological and pedagogical separation that affects learning and has to be overcome by the dialogue (higher order interaction). Anderson and Garrison [3] proposed the Equivalency theorem assuming that in order the learning to take place, one of the interactions shall be at a high level. Other dyads of interaction can add value and increase the quality of learning but it must also estimate the costs of resources for these types of interactions.

The uptake framework [2] assumes that interaction is fundamentally relational, so the most important unit of analysis is not isolated acts, but rather relationships between acts. The uptake framework attempts to deal with on the following analytical challenges in distributed learning environments, which are also relevant in DLEs:

- Interaction may be distributed across actors, media, space, and time.
- There is a need to examine the sequential organization of interaction with-in learning episodes.
- It is not correct reducing the sequential history of interaction to the most recently occurring event category – it is needed capturing the aspects of the coherence of the mediated interaction that are not apparent in the threaded structures.
- There is a need to scale up analyses to more episodes and larger scale organization.
- Properties of distributed interaction place different demands on representations of data and analytic structures - analysis of interactional processes must reassemble interaction from the separate records of multiple media, but remain media aware to record how people make use of the specific affordances of media.
- An analytic program must be based on theoretical assumptions concerning what kinds of research questions are worthwhile - analytic representations should minimize assumptions concerning the answers to the research questions posed.

The uptake framework [2] attempts to provide a new methodological framework for the analysis of inter-subjective meaning making. The framework includes a media independent characterization of the most fundamental unit of interaction, which they call uptake. Uptake is present when a participant takes aspects of prior events as having relevance for ongoing activity. The concept of uptake supports diverse definitions of "interaction," including any association in which one actor's coordination builds upon that of another actor or actant. Uptake can be refined into interactional relationships of argumentation, information sharing, transactivity, and so forth. The contingency graphs serve as abstract transcripts that document relationships between events. They capture the potential ways in which one act can be contingent upon another. Contingencies provide evidence that uptake may exist, but do not automatically imply that there is uptake. For example the following contingencies may be found: media dependency, temporal proximity, spatial organization, semantic relatedness, inscriptional similarity. The analyst interprets sets or patterns of contingencies as evidence for interaction.

4 Dippler - a DLE with an Ecological Learning Analytics Approach

We have built a prototype of DLE called Dippler [19] which consists of three interconnected core components: a central learning flow management service, institutional course management environment and a personal blog-based e-portfolio for each learner. Learners can extend their personal learning space by integrating external social media tools, services and content to their e-portfolios through simple technologies such as RSS-feeds, embedding, linking and widgets.

While in LMS (e.g. Moodle) all learning interactions take place within a single closed Web information system and the data is stored in one centralised database, the situation changes radically in distributed DLEs. In order to add learning analytics functionalities to DLE like Dippler, two necessary steps must be taken: (1) harvesting, storing and monitoring interaction-related data with rich semantics from distributed systems that DLE consists of and (2) identifying methods and tools for analyzing and visualizing the data.

Most of the tools for gathering the learning analytics data [11, 20] are directed to the closed LMS systems, while the most of the learning happens outside the LMS. Cohere [21] is another analytic tool that deals with the discourse network analysis and break down the learning interaction analytics to a discourse unit. The GLASS tool suggested by [22] for learning analytics visualization captures data from different computer applications but does not provide the data recorded in a the form of interactional dyads and is restricted only to learner-content interaction. We argue that a holistic, automated and event oriented unit of analysis must be a focus in learning inter-action analytics.

Ferguson and Shum [23] propose a notion of SNLA - social learning analytics and after reviewing different types social learning analytics (social learning network analytics, social learning discourse analytics, social learning disposition analytics, social learning content analytics, social learning context analytics) offer visualizations and recommendations to support learning. They introduce a SocialLearn media space specially accustomed to learning. This environment is a good example of combining different social learning analytics and this way might seem like a good idea for improving learning, it cannot offer learning interaction analytics data for automated semantic learning analytics and especially for studying the depth and quality of interaction.

Lehman et al. [24] use two distinct approaches to study "off-topic" that is regarded as a part of a dialogue that has no pedagogical value. First they recorded tutoring and introduced coding schemes, that were later categorized into three pedagogically-relevant groups: Tutor Motivational Dialogue Moves, Tutor Pedagogical Dialogue Moves, and Student Dialogue Moves. The other approach deployed Linguistic Inquiry and Word Count Tool. The authors conclude that these methodologies seem to sup-port the initial casual observations that the "off topic" is not simply another category. That the "social exchange" cannot be categorized as simply "other" and this type of exchange also serves a pedagogical value. Although this research combines different approaches and tries to analyze to the depth and quality of one particular type of interaction, it is clear that the question on automated interaction analysis as well as scaling up the results remains.

Krüger et al. [25] give a similar unit of analysis and architecture of a tool for structuring and exporting data, relevant to our work, what they call a Schema i.e. data model that captures the essence of the event - Actor, Verb, Object, Timestamp. But this work is mainly based on the traditional LMS data (view/submit frequencies and quiz scores) and uses association rules instead of exploratory sequential data analysis. Just like many other experimental products, this tool might be interesting for researchers, but it would be a challenge to make it meaningful and usable for an average teacher in a domain other than computer science.

In the open DLEs the activities happen in the user environment and the interaction patterns can be traced only based on the logs retrieved from those environments, therefore the monitoring of the interactions and logging data needs to be designed having a predefined theoretical foundation. The ecosystem approach in Dippler considers an upside down roles where the “species” or “organisms” (i.e. users, content, tools) interact with each other and the broader technological landscape and socio-cultural contexts make up the environment. In this sense there must be an analytical system for learning interaction, a system where the interaction can be analyzed within the ecosystem approach of distributed learning.

Common analytical practices of coding and counting interaction types for statistical analysis that are prevalent in TEL literature obscure the sequential structure and situated methods of the interaction [2]. In order to analyze the learning interactions in DLE, it is necessary to model the patterns of interactions and record the related data in real time in a way it could be easily used for learning analytics.

Harvesting, storing and monitoring the data on learning interactions poses challenges due to the very nature of DLE concept – it’s a distributed learning environment where different social tools are selected, used, added and removed from the learner side. Four types of learning interactions take place in such settings: learner-teacher, learner-learner, learner-content and content-content (e.g. aggregators). The current version of Dippler documents these interactions in the form of Activity Stream, which is based on the pedagogically enhanced Activity Base Schema (activitystrea.ms). Dippler’s Activity Stream displays the main types of interactions in the form of a proposition, containing the Actor (a user), the Action (a verb from restricted vocabulary), the Object (a target of the Activity) and timestamp. The approach resembles to one proposed by TinCan API or xAPI, which makes two activity stream technologies easily interoperable.

The Experience API is a service that allows for statements of experience (typically learning experiences, but could be any experience) to be delivered to and stored securely in a Learning Record Store. The Experience API is dependent on Learning Activity Providers to create and track learning. Learning ActivityProvider is a soft-ware object that communicates with the LRS to record information about the learning experience. Learning activity is a unit of instruction, experience or performance that has to be tracked. A Statement consists of <Actor (learner)> <verb> <object>, with <result>, in <context> to track an aspect of a learning experience. Several statements can be used to track the whole experience. The statements are recorded in the LRS - Learning Record Store [12].

As most of the Objects and Activities in Dippler are annotated with the domain-related categories (keywords structured as taxonomy), it opens the potential for a different kind of learning analytics not currently supported in the traditional LMS. In order to support multi-level, multi-theoretical analysis of learning interactions in Dippler, we decided to adapt its interaction-monitoring component to make it compliant with the uptake framework introduced by [2].

The uptake framework examines the interaction in the distributed learning setting. It views the analytics of the interaction in the hierarchical structure. The hierarchies start with traces and domains – the unit already readily recorded in forms of events through the Learning Activity Streams using adapted version of xAPI.

With the help of recorded dyadic interactions in the forms of events it will be easier to create an automated analytic system that will scale up the interaction analytics. Also, it will solve the problem with identifiers that is brought up in the uptake framework [2]: '*A key concern is persistence of identity across tools and sites: some work may be required to ensure that each given actor is represented by the same identifier in the event model, and likewise for the identity of digital objects shared across tools (ideally persistence of identity should be addressed in mash-ups for the learners' sake. Once this has been accomplished, the event and domain models taken together provide an abstract transcript of the data that re-assembles in one analytic artifact the diverse events that were for their actors a single activity*'.

So the uptake framework combined with adapted Activity Streams can offer the following advantages:

- Recording interactions in dyadic events will encompass the processes, traces, domains.
- The relations with a domain will be already identified through annotation, entities and their relationships established and recorded.
- Enable recording the activities happening outside the LMS, so it will support the concept of distributed interactions [2].
- It will make the learning interaction analytics automated.

5 Sample Scenario: Collaborative Concept Mapping

Let us illustrate the discussion above with a fictional scenario, involving a service-species based on a didactical method called collaborative concept mapping. This method involves engaging students in a small group work, where a concept mapping tool is used for identifying the core set of concepts for a given domain along with and their relations with each other. This scenario belongs to a set of design artifacts, which were created to conceptualise and guide the process of development of the learning analytics module for Dippler.

In our sample scenario, teacher gives an assignment to the students in Dippler platform, while connecting the assignment explicitly with a specific learning outcome. As each learning outcome is previously annotated with 2–3 keywords from domain ontology, the Dippler connects all related learner interactions also with these keywords. In the given case, the assignment is: "Form the groups of 2–3 and identify core concepts related with digital competence and their relations, so that it would be compatible with three digital competence standards. Read the Chap. X from the course textbook and compare three given digital competence standards. Output of your group work should be submitted in the form of a concept map that includes initial set of concepts".

Student groups start working on the assignment in their personal learning spaces, the blogs that communicate to the BOS service of Dippler all interactions. Each student separately identifies the set of concepts and reports about them in his blog, students can monitor each other's blog posts and comment each other's work – the goal is to come to the common ground about which concepts should be used in the concept map. In this phase some teachers like to comment students blogs, whereas others don't intervene to the process and wait only for the final assignment result. Next, students start working with the shared concept map in a Web-based tool Bubbl.us, using this set of concepts, and they use Skype for discussing while they work. Final concept maps are submitted as assignments by each student group. Extended xAPI record for such interactions are documented in the following format:

In <Context>, <User> performs <Action> on <Object> with <Tool> producing <Result> at <Time>. For instance, a specific line in the record might look like this:

In **Assignment 3**, **John adds** a **comment** to **blog postX** with **toolX** at **12:30 12-07-13**. All the xAPI records related to this assignment are then passed to the learning analytics module of the Dippler, which returns an overview of interactions, recommendations and feedback in the form of diagrams.

The success of this assignment in different groups may be monitored and analyzed using the ecosystem principles and fed back to the groups:

- How many learning services of support are available at different time moments of the activity and is there a variability – are some support comments more effective and more fit than others; is there a competition between them on user attention or do they complement each other, for example, when student comments appear seldom, teacher's comments become more frequent and vice versa; How well are different learning services of support interconnected into network (for example by push and pull and mash services between student blogs and Dippler), and how does this affect the network permeability, keep the learner attention and enable the formation of coherent group understandings;
- How do different support service "organisms" enable the feedback loop to and from the ecosystem – what is the impact of support comments with different life-span on the formation of coherent group understandings – those that are stored in blogs, and the same comments when they appear mashed way on Dippler wall for monitoring the group work or the comments shared via Skype;
- How well do different support services send signals to each other of their presence, abundance in the current time moment in the ecosystem – this may enable synergy between them, and for the group members and teacher it gives the feedback whether the team is active or it would need prompting for creating a coherent understanding.

6 Conclusions

This paper proposed a new approach to learner interaction analysis, especially through new methods of data collection and analysis inspired by connecting multi-level, multi-theoretical uptake framework with key principles of digital learning eco-systems and capabilities of Experience API. The next steps of our research will implement and validate empirically our learner interaction analytics framework and related technological solution as an integral part of Dippler DLE.

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Observing the Use of e-Textbooks in the Classroom: Towards "Offline" Learning Analytics

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Abstract. Learning analytics is an emerging approach that is equally popular among researchers and educators-practitioners. Although the methods and tools for LA have been developing fast, there still exist several unsolved problems: LA is too much data driven, weakly connected to theory and is able to analyse only the activities documented in an online setting - in LMS. We propose a solution for the LA unit of analysis drawing upon the research of existing practices and tools used for offline contexts: the data is coming from the physical learning interactions based on the observations in the classroom setting and captured with classroom observation application. We argue that if the unit of analysis has a particular logic and structure, it can unleash the possibilities for "offline" analytics that can be later integrated with online LA.

Keywords: LEARMIX · Learning analytics · eTextbooks · Unit of analysis · TinCan API · xAPI

1 Introduction

Textbooks have been playing an important part in teaching and learning in the formal education context for more than one century. As the textbook publishers, editors and authors are the most careful readers and implementers of curricula and subject-related news, the textbooks have gained large impact in educational development. On the other hand, widespread use of printed textbooks is hindering the advancement of modern learning analytics, as the learning activities that take place outside of digital realm leave no digital trace behind. Emerging e-textbooks might change a lot in that sense, but it depends on the approach taken in e-textbook development. Currently, the majority of e-textbooks are released either as e-books (in epub, mobi, pdf formats), apps or content packages integrated into online course (e.g. SCORM or CommonCartridge). In most of the cases, only the latter format allows acquiring rich data about learning interactions in a standardized format. LEARNMIX project in Tallinn University aims at exploring alternative forms for e-textbooks of the future that should support innovative pedagogical scenarios and advanced learning analytics. But even if most of the textbooks and other learning resources will be turned into digital format, there will remain many learning activities that will take place in the physical classroom setting without leaving any digital trace behind for learning analytics. The research problem addressed by this

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exploratory study was to find out the existing approaches and tools for collecting learning analytics data in the offline settings.

2 Unit of Analysis in Education and Computer Supported Collaborative Learning

When addressing research questions, it is important to have a consistent and theory driven unit of analysis. The discussion on the different *units of analysis,* approaches and developments throughout centuries and the philosophical stances they take on is important when it comes to learning analytics and its *unit of analysis.*

Educational research concentrates on different *units of analysis*; Stahl [1] discusses the issue of *unit of analysis* in cognition that had different foci in different times: *concepts* (Plato), *mental and material objects* (Descartes) (and relationship between them), *observable physical objects* (empiricism), *mind's structuring categorization efforts* (Kant). All of the approaches dealt with the inner functions of an individual mind. Hegel entered the discussion with a larger unit of analysis – which was historically, socially and culturally determined.

Hegel's philosophy shaped three mainstream schools of thought – Marx (critical social theory), Heidegger (existential phenomenology) and Wittgenstein (linguistic analysis). To Stahl, these three main directions influence how the CSCL units of analysis are formed: For Heidegger the unit of analysis was the *man with unified experience of being-in-the-world.* Wingenstein entered the discussion with the *unit of analysis* from *mental meanings* to *interpersonal communications in the context of getting something done together.*

In some cases CSCL research takes socio-cognitive or socio-cultural approaches. But in both cases the *unit of analysis* is mostly *an individual mind*. Engestrom is the one taking the unit of analysis to the whole *activity system*. But to Stahl's understanding Engestrom's theory is not interested in group knowledge building but rather with organizational management of the group. Influenced by Marx, theory tries to see societal issues in the making. Even in distributed cognition, which deals with group-cognitive phenomena, mostly socio-technical systems and highly developed artifacts are analyzed [1].

3 Learning Analytics: The Concept, the State of the Art

One of the leading definitions of learning analytics suggests that it is *the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs*. This definition had been set out at the 1st International Conference on Learning Analytics and Knowledge [2]. The field is still emerging, rapidly developing and experiencing *a gradual shift away from technology towards an educational focus*, while the three main drivers for learning analytics have been defined as technological, pedagogical and political/economic [3].

These drivers are conceptualized by Ferguson as challenges [3]:

- Big Data - a challenge for its volume, difficulty to handle the interaction data and most importantly extracting value from the big data-sets.
- Online Learning that poses an educational challenge - how to optimize opportunities for online learning.
- Political Concerns - how to improve learning opportunities and results at different levels?

According to Ferguson the drivers draw attention to the three groups of interest - governments, educational institutions and teachers/learners. The development of learning analytics shifts the balance between the three drivers and three groups.

Greller and Draschler give a general framework of learning analytics [4] and offer considering six critical dimensions within the research lens. Each of the dimensions can have several values and it can be extended upon a need. Represented dimensions are: stakeholders, objectives, data, instruments, external constraints and internal constraints.

Greller and Draschler also give a model of information flow between the stakeholders and it is based on a common hierarchical model of the formal education. A pyramid view (with the learner as a cornerstone) is illustrating how data analysis from lower layer can inform the above layer. According to Buckingam Shum the convergence of the Macro, Meso and micro levels is the key to the successful learning analytics [5].

3.1 Units of Analysis in LA

When we are to consider what has to be analyzed and what information do we need to infer using LA, firstly, the level of learning analytics must be defined. The interest groups may overlap but different granularities are needed for different groups: *The choice of target audience affects how researchers conceptualize problems, capture data, report findings, predict what will happen, act on their findings and refine their models* [3]. Within the context of our research interest the micro-level, teacher/learner learning analytics should be directed to the activity, an event consisting of interaction between **a subject** and **an object** that are bound with **a verb.** There is a need for theory driven, event oriented unit of analysis [6, 7].

Suthers et al. with the uptake framework proposed that the event is the core for analyzing data and understanding which interactions lead to learning [9]. The *Uptake Framework* [7, 9] assumes that interaction is fundamentally relational, so the most important unit of analysis is not isolated acts, but mostly relationships between acts.

Conceptualizing the Uptake Framework hierarchies and the possibilities of learning analytics, it has also been suggested to view Learning Flow as a main unit of analysis for the learning interaction analysis [7].

3.2 Limitations of LA and Potential of xAPI

Most of the tools for gathering the learning analytics data are directed to the closed LMS systems, while the most of the learning happens outside the LMS - in distributed setting or offline part of the learning which is most of learning. Currently, LA covers only the part of the learning that happens within the LMSs. In most of the cases, LMSs data is harvested and analyzed. The problem is that it is not enough. Siemens believes, that LMSs are adopted as learning analytics tools and reflect the learner's interactions within a system. The capabilities of tracking and visualisation of interaction data has also been limited [3, 8].

The similar problem persists with the physical world i.e. offline "data" - library uses, learning support, in case of blended learning - the part of the learning that happens outside of LMS, online or offline. Long and Siemens suggest mobile devices as prospects of "*bridging the divide between the physical and digital worlds*" [8].

One way of dealing with the limitations of leveraging the data from the settings outside LMS is to explore potential of Experience API [10]. The Experience API is a service that allows for statements of experience (typically learning experiences, but could be any experience) to be delivered to and stored securely in a Learning Record Store. Learning activity is a unit of instruction, experience or performance that has to be tracked. A Statement consists of <Actor (learner)> <verb> <object>, with <result>, in <context> to track an aspect of a learning experience. Several statements can be used to track the whole experience. The statements are recorded in the LRS - Learning Record Store [10].

Another problem with learning analytics within the limits of the current development is a weak connection to theory. This limitation of data monitoring and harvesting could be overcome by having a particular theory in mind before recording the data [7].

Our paper targets the "offline" analytics dilemma and explores the potential of xAPI and Uptake Framework working together towards a new type of *unit of analysis* in the context of learning analytics.

3.3 Ethical Considerations

It should not be argued that the privacy of the data subjects must be protected. There are several factors influencing the process of protection that can work against individual freedoms (if privacy is abused) or restrict using the full potential of LA. We believe these two factors shall be balanced. According to Hilderbrandt [11], the core of privacy must be found itself in the idea of identity and this is not only because of the advancement of high-tech identification technologies but also because the process of identity building can harm the privacy of individuals.

Slade et al. [12] believe that students shall be involved in the data harvesting and analysis. According to Kruse et al. [13] there should be a "student-centric", as opposed to an "intervention-centric", approach to learning analytics. This suggests the student should be seen as stakeholders of their own data. And also as co-interpreters of own data - and perhaps even as participants in the identification and gathering of that data. Greller et al. [4] list the ethical side of the use of personal data in the external limitations of learning analytics.

Based on the literature overview, currently we may refer to some of the solutions for data privacy protection: 1. Involving students [data subjects] in the process, make it transparent and make it a student analytics. 2. Anonymization/deidentification of data. 3. Consent forms.

4 eTextbook Analytics

4.1 Studies on eTextbooks Use

According to Baek et al. [14] *in order to effectively support students' learning, it is important to comprehend students' experiences using eTextbooks*. There are several possibilities to understand the patterns of use for future inferences – 1. For the deployment of appropriate pedagogic strategies 2. For student self-reporting 3. For decision making processes – in terms of the design and etc.

Research on the use of eTextbooks mainly focus on the issues of satisfaction of use, preference of use over traditional textbooks and other factors [15–18]; The study conducted by Baek et al. [14] in the various campuses of US focuses on the understanding of students' eTextbook use experiences. This study used surveys to assess students' perceptions of the eTextbook in terms of satisfaction and ease of use. Cutshall et al. [17] also assessed perceptions on the use of etextbooks and web-based homeworks. When assessing the use of eTextbooks logs were only used to understand student reading behaviors (number of page prints) and correlated to the satisfactions of use [18].

An example of analytics in eTextbooks is a research conducted by Nicholas et al. [19] using the data from digital footprints on (a) volume, duration and timing of use; (b) where use took place; (c) individual book titles used; (d) location of use; (e) type of page viewed; (f) institutional and subject diversity; (g) scatter of use; (h) nature of use; and (i) method of searching/navigating. The log data were analysed to describe how users interacted with the system. The authors, though, conclude that *logs only provide us with a very superficial idea of who the e-book users were (their institutional affiliation was known), so for a better picture we have to turn to the questionnaires.* Khurana et al. [20] deployed text analytics to assess the coverage, readability and comprehensibility of eTextbooks. They use different units of analysis: sections, bookmarks, topics, sub-topics.

Having a goal to build an open source online eTextbook for DSA courses integrating textbook quality text with algorithm visualization and interactive exercises, Fouh et al. [21] concentrate on the development of a OpenDSA interactive eTextbook where they also incorporate a kind learning analytics – mainly for the self-reporting for students, and also inferring meaning from student-content interactions for "studying the pedagogical effectiveness for various approaches and support for gathering data about usability of system components for future improvement. So the unit of analysis is mainly student-content interaction centered. The study on the use of the eTextbook was aimed at the student perceived satisfaction evaluation and a test whether the eTextbook helped reduce the grading burden.

Studies on eTextbook use are developed around the ideas of satisfaction of use or reading behaviors. *Units of analysis* are individual student perceptions and sometimes student-content interactions to gain insight on reading behaviors, not the analysis of the design or pedagogical rationale behind it. Very often, when the study aims at uncovering the learning design principles of an eTextbook, it does not refer to the possibilities of learning analytics as for instance, in case of the study of Choi et al. [22].

4.2 Offline Learning Analytics: Observing the Use of Textbooks in the Classroom Lesson Observation Apps: Critical View

Two different approaches can be used in the eTextbook use observations: taking advantage of online data coming from clicks, resource access etc. and “offline” analytics with its wide range of possible interactions, written in different statements and formats.

Classroom observation apps are very useful tools for recording classroom learning interactions on the use of textbooks in “offline’ settings. For this particular observation study we overviewed and compared 6 classroom observation apps based on particular requirements. These applications are: LessonNote, iObserve, Observation 360, iAspire, GoObserve, SCOA. Applications were chosen according to their free access to at least demo versions.

The applications were compared considering several features: 1. Interface affordances 2. The ways of input 3. Pedagogic scenario/model 4. Output of the generated data 5. Possibilities of analytics and most important part of our research scope 6. Units of analysis. The features were chosen based on the importance to the scope of the research. The table describes the proportion of certain features used in those applications (Table 1).

Table 1. Application comparison

Feature	Value					
Interface	Tapping .6	Drag&drop .1	Sliders .3			
input	Handwritting .09	Typing .36	Photo .27	Audio .09	Video .09	Other .09
Scenario/ model	Based on a spec.model .5	Based on several models .33	Flexibility of switching models 0	Neutral .17		
Output	.pdf .25	Cvs .0	Word .08	Email .42	database/ cloud .25	
Analytics	No analytics .31	No datasets .15	visualisations 0.31	datasets/ cloud .3		
Unit of analysis	individual/ teacher .43	individual/ student .14	Event/activity .07	Group .07	Class .29	individual/ teacher .43

Based on the overview LessonNote app was chosen for it represents the closest possible app to what we have envisioned for the use in observations, namely for its event-driven *unit of analysis*.

5 Empirical Study

In the remaining part of the paper we will describe our effort to use a LessonNote application for supporting the collection of offline learning analytics while observing the use of textbooks in the classroom settings. We will continue with analysing and demonstrating benefits and drawbacks of LessonNote application for recording offline learning analytics. The study mainly focuses on the *unit of analysis* and its importance in the “offline” analytics based on the classroom observation application.

5.1 Method and Sample

In the context of Learnmix project we carried out an intervention study in K-12 education. Our aim was to intervene into current teaching and learning practices with the purpose to enable learners to become actively engaged constructors of their own experience and knowledge by creating, modifying and integrating various physical, and digital artefacts. For that we designed five different scenarios (flipped- classroom, project-based learning, game-based learning, inquiry-based learning, problem-based learning) for teachers to choose from and implement it in her/his lessons. In these scenarios the role and use of textbooks changed from textbooks as an object of knowledge construction to textbooks as a source of inspiration, etc. We have to mention here that we do not treat the aforementioned list of scenarios as a definite one, but rather as a starting set of potential scenarios for enabling students to become constructors of their own experience and knowledge in the midst of the digital transformation.

We observed 12 lessons in 6 different K-12 schools. These schools were chosen because of their more advanced IT infrastructure and teachers with open-minded learning and teaching practices. For documenting the flow of a lesson and emerging interactions we made use of LessonNote application. LessonNote application allowed timing, recording photos of student work and activities, which were inserted into the notes; and creating seating charts. As an additional tool we video recorded all the observed lessons. For the research described in this paper the videos didn’t play an essential role.

For understanding the use of (e-)textbooks in the aforementioned scenarios we created a framework for extracting the statements of students and teachers’ experience (learning flow) in a similar way to Experience API. Our framework consists of three main items:

1. Actors - a teacher or student(s) specifying whether the activity was done in groups, peers or individually.
2. Artifacts - artifacts were divided into three groups:

   – Display artifacts are physical objects in the classroom (for instance computer, projector, screen) whose function is to display conveyor artifacts. Display artifacts themselves are not representations of knowledge, but are seen as carriers for other artifacts.
   – Conveyor artifacts are various applications, which support the mediation or creation of knowledge representations (for instance iBooks, Prezi, Weblog, etc.). The affordances of conveyor artifacts very often define potential actions.
   – Content artifacts are representations of knowledge displayed in different formats (for instance text, video, image), which are created by professional textbook authors, by teachers, by students or others.

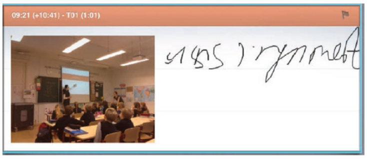
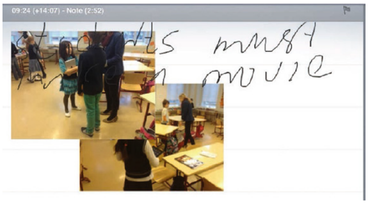
3. Actions - actions performed by a teacher or student(s) during the learning experience.

Such a framework allowed us to focus on specific actions and every accompanying (digital) artifact used or created before and during the learning experience. Furthermore, for our intervention study it was important for us to determine the role of students and teachers in learning experiences (whether a teacher or a student is a creator of an (digital) artifact, whether a student takes control and responsibility for what he/ she is doing, etc.).

5.2 Results and Discussion

We implemented our analytical framework to our data set extracted from LessonNote application and video transcript. Despite of its many useful affordances, such as allowing recording activities according to timeline, shooting photos and adding them to a particular activity, LessonNote application also has some deficiencies. With the following 2 examples we demonstrate the deficiencies of LessonNote application as a tool for supporting the collection of offline learning analytics and translating its data into a form that supports Experience API statements and Uptake framework (Table 2).

Table 2. Results

Activities	LessonNote activities	Video transcript: (Subject verb object)
Teacher activity		Teacher organizes class **Teacher gives assignment** Teacher forms groups
		Group A moves out **Group A organizes tools** Group A starts a discussion

In the table we presented examples from the LessonNote app aligned with data coming from video transcripts. Video transcripts were produced by two researchers putting in the matrix compatible with xAPI statements. The examples brought here demonstrate how the LessonNote app captured activities and what can be extracted from videos. LessonNote captures one particular activity (shown in bold) and with video and later analysis it is possible to capture *preceding* and *proceeding* activities with the LessonNote captured activity encapsulated by the two (and more). But also this is to show that it is possible to structure the data in the form of Experience API compatible statements.

5.3 Conclusion and Future Work

The intervention study showed that it is possible to transcribe the interaction data in the form of statements, but recording "offline" interactions with LessonNote app did not offer satisfactory results for several reasons:

1. It proved to have interface problems – it is not possible to handwrite data as it is happening in real time.
2. It does not capture nested activities.
3. It does not allow quick documentation of activities.
4. It has no enough affordances, for instance it is not possible to define/form groups and assign numbers for later analysis.
5. Though it more or less focuses on event as a unit of analysis, it does not give full possibilities to automatize the process.
6. It does not show the dyadic interactions - who is interacting with whom.

Based on the overview of classroom applications and the empirical study we plan to develop a classroom observation application to be used on offline observations and learning analytics. This application will cover the gaps and offer "offline" analytical features that can potentially be aligned with online data. The application will be based on the overview of the similar applications and xAPI statement and event-driven *unit of analysis.*

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How to Aggregate Lesson Observation Data into Learning Analytics Dataset?

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Abstract. The technological environment that supports the learning process tends to be the main data source for Learning Analytics. However, this trend leaves out those parts of the learning process that are not computer-mediated. To overcome this problem, involving additional data gathering techniques such as ambient sensors, audio and video recordings, or even observations could enrich datasets. This paper focuses on how the data extracted from the observations can be integrated with data coming from activity tracking, resulting in a multimodal dataset. The paper identifies the need for theoretical and pedagogical semantics in multimodal learning analytics, and examines the xAPI potential for the multimodal data gathering and aggregation. Finally, we propose an approach for pedagogy-driven observational data identification. As a proof of concept, we have applied the approach in two research works where observations had been used to enrich or triangulate the results obtained for traditional data sources. Through these examples, we illustrate some of the challenges that multimodal dataset may present when including observational data.

Keywords: Multimodal learning analytics, learning sciences, classroom observation,

1 Introduction

Learning analytics (LA) is an interdisciplinary field mainly based on data coming from digital traces and digital realms. In order to understand and optimize the learning process, researchers pay especial attention to what is happening in computer-mediated contexts. However, the evidence gathered might be incomplete in real-world learning activities where there face-to-face and digital spaces are frequently combined [1], [2]. Multimodal learning analytics (MMLA) may be a promising approach for this kind of contexts, since researchers in this area are trying to identify and collect also real-world learning data [1]. In addition to the data sources compiled by Blikstein & Worsley in their state of the art [9] (such as speech signals, text-based and graphic-based content, or gestures), we argue that classroom observations of real world teaching and learning processes could be a relevant data input. Moreover, observations that capture teacher pedagogical intentions are highly relevant information that can become a core of the analysis.

Research has shown that triangulating pedagogically grounded LA with teachers' observational data can be effectively used for teacher orchestration and research purposes [3]. Although there are multiple tools that support the observation process like Kobo Toolbox[1], FieldNotes[2], Ethos[3], Followthehashtag[4],Storify[5],and VideoAnt[6], to the best of our knowledge, there is no one that enables the integration of the observations with other data sources for later analysis.

From the theoretical perspective, there is a need for frameworks that take into consideration the pedagogical semantics in the data collection, integration and analysis. In addition, from the technical point of view, questions remain open about how to model, collect, and integrate the evidence when heterogeneous data sources used. Therefore, we hypothesize that the LA community will benefit from having an integrated solution that aligns pedagogical semantics with xAPI statements.

This paper proposes, first, pedagogy-aware observational data identification approach. To assess its validity, we have chosen existing research that used observations in combination with LA for different purposes. In order to verify whether the approach could be suitable for these cases, we have applied the approach to the observations of such works. Through this proof of concept, we have identified a set of challenges to be overcome when integrating observations with other LA data.

2 Related Work

Learning Analytics and educational Action Research are two research areas with similar goals (while the former uses educational data to foster learning, the later aims to improve the teaching practice), but different methods (LA draws from automatically collected data, and Action Research from observations) [5]. Thus, the combination of both could contribute to improvement of LA research and practice [6], e.g., by mitigating the lack of proper theoretical and pedagogical foundations of existing LA solutions [4].

The alignment between LA and Action Research entails the integration of observations as part of data sources used in the analysis. This step could have a clear impact on the analytics accuracy and representativeness. In most of the cases, part of the teaching and learning processes are not supported by technology. As demonstrated by some authors [12], enriching the datasets with observational data could contribute to

1 http://www.kobotoolbox.org
2 http://fieldnotesapp.info
3 https://beta2.ethosapp.com
4 http://www.followthehashtag.com
5 https://storify.com
6 https://ant.umn.edu

obtain a more realistic view of the educational scenario. However, the implementation of such enrichment is not trivial at different levels:

- Data gathering: The lack of guidance in classroom observation applications leads to unstructured and pedagogically neutral data with no consistent format [13].
- Data integration: Most of the LA solutions involve a limited number and variety of data sources [2] [7] [8], mainly due to the heterogeneity of data models, formats and granularity [10].
- Data analysis: The process of manual coding usually followed by the analysis of the observations is time-consuming and ineffective [13].

In the following section, we propose an approach that tackles the aforementioned problems from a theoretical point of view. Afterwards, the approach is applied to two research studies in order to verify whether it could support the data gathering, collection and integration of the observational data.

3 Theoretical Inquiry: Towards a Solution

Three dimensions were taken into consideration in the design of our approach, namely:

- The philosophical and research approach that frames the purpose of the LA study;
- The educational theory and the pedagogical background that sustains the learning scenario;
- The technological and architectural aspects that condition the data gathering and integration of multiple and heterogeneous data sources;

This section introduces each dimension, reflecting on those areas when the different dimensions overlap. Afterwards, we describe how this approach affects the data gathering, integration and analysis.

3.1 The Approach

Philosophical approach. Current data gathering and analysis proposals can be classified in two main coarse-grained sets. Data-driven generate indicators in a bottom-up fashion, based on available data. Conversely, model-driven approaches need pre-specified models that guide the data gathering and analysis in a top-down process. No matter which approach is followed, the selection and definition of the unit of analysis plays an essential role. Indeed, the **unit of analysis** is used a critical instrument to dismiss one approach or another [14]. Since the unit of analysis has to also be manageable [15] and appropriate for its purpose [14], it is therefore important to have a consistent unit of analysis for multimodal learning analytics.

Technological context. Research in this field has suggested that it is possible to organize several heterogeneous data sources in the form of the xAPI statements and analyze them with a specific framework in mind [11]. xAPI has a logic and syntax -*actor-verb-object-* that closely follows grammatical categories of most of languages as *subject-verb-object* (in a context).

Educational Theory. In our research, from philosophical point of view, we follow a constructivist approach. Thus, the goal is to enable learners to become actively engaged constructors of their own experience and knowledge. This motivation triggers our interest for understanding the learning activity. In order to track constructivist learning activities, xAPI is ideally suited [18]. While *actor* and *verb* concepts are straightforward in xAPI statements, the *object* has led some researchers to think that is necessarily a Vigotskyan *activity system* [18][19] unit. In fact, this sentence-like specification is quite neutral in its essence, since the object is simply an object and not an "object of activity" [20] as claimed previously. This does not mean that, if we want to use activity theory for data collection and analysis, the object cannot become an "object of activity". This leads us to argue that xAPI statements are not pedagogically biased. Indeed, they can be used to aggregate data with different semantics that are aligned with the pedagogical intentions.

Figure 1 shows how the three different dimensions of our approach intersect. The **unit of analysis** is modeled to be pedagogically neutral**,** semantically open (vocabulary is interchangeable), and system-independent. In this way, this unit of analysis will allow us collect data with different pedagogical semantics and integrate it, later on, with other data sources. In this approach, the learning event is the unit of analysis [16], which is expressed using xAPI statements.

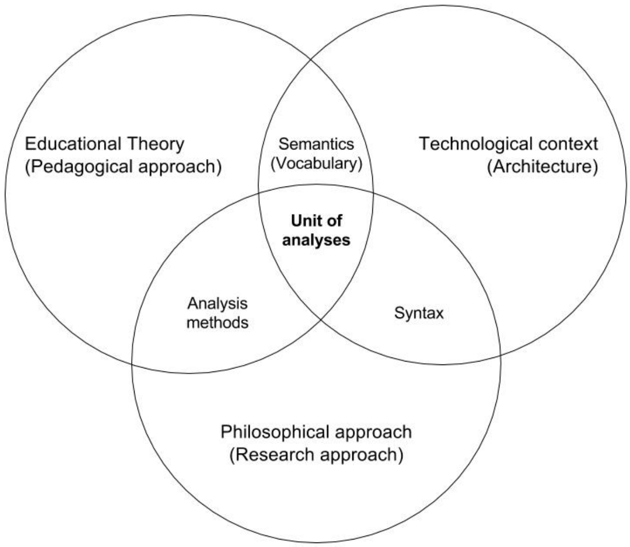

Fig. 1. The approach explained

3.2 The Approach in Action

The observation process is supposed to be carried out by an ad-hoc observer or any participant of the scenario, especially the teachers. The process will be supported by a classroom observation application implemented according to the approach presented in the previous section.

To better understand how the approach would be applied, we describe it through the steps of the common protocol that guides the observation process:

Step 1. Be aware of the elements that belong to the learning context. To facilitate the data gathering (seen as an observer's task) and to enable the integration, it will be necessary to register in all the actors and objects in advance. In that way, the observer will be able to link the events to the corresponding actors and objects. A first implementation challenge will be to know in advance not only about the actors and objects but also to extract the corresponding identifiers which are necessary for later integration and analysis across data sources. To solve this issue, some authors proposed to use the learning design and its instantiation in the technological environment as description of the context [12]. However, this solution is not flexible enough for learning scenarios where new participants or objects may emerge during the activities.

Step 2. Define the areas of focus, the indicators to be obtained in order to illuminated such areas, and the specific events to be observed. We should not forget that we envision the observations as part of a multimodal dataset. Thus, it will be necessary to define, as a whole, how the different areas of interest are informed by the data sources available, and the trackable events. In the case of the observations, the application will be loaded with the vocabulary necessary to describe the events (xAPI verbs).

Step 3. Collect observable events. In this case, the observations will be recorded following the *subject-verb-object* structure, using the set of previously loaded subjects, verbs, and objects. These events will be presented as xAPI statements that will be timestamped and sent to a learning record storage together with the rest of the multimodal dataset. It should be noted that a first study was already carried out to ensure the whether it was feasible to register the observations following the aforementioned format [13].

Step 4. Analyze and interpret the results. The observations will be analyzed with the rest of the events tracked by the complementary data sources, extracting the indicators previously chosen for the different areas of focus.

To better support the integration with other data sources we expect to explore the definition of vocabularies and xAPI Recipes that help us to take also into account the context as suggested by Bakharia et al. [19]. Recipes are set of rules that govern how to use xAPI so that we can ensure, first consistent data to describe similar activities from different sources, and second interoperability across systems.

4 Proof of Concept

To illustrate the potential of our proposal, we have identified 2 research papers that make use of both observations and LA. This section provides a proof of concept of how such research could benefit from an application that implements the approach described in section 3.

Case 1: The first paper describes a study where the teacher reflects on the aspects to be evaluated in a learning scenario, selects the data sources that are relevant for each aspect, and finally choses the events to be used in the LA process [2]. As part of the data sources, the teacher decided to include her own classroom observational data. The events registered by the teacher were specified in advance and covered: the students who attended the face-to-face sessions (which were mapped with activities), the students who had submitted the productions associated to each activity. The teacher registered the events manually using Google Spreadsheets and ad-hoc solution had to be implemented to retrieve the evidence, translate it into a machine-readable format, and integrate it with the rest of the data sources.

Case 2: The second research paper applied a multiple data gathering techniques for triangulation in a face-to-face course supported by technology (observations, questionnaires, logs, and learning outcomes in the form of text) [21]. An observer attended the course in order to register the face-to-face interaction. Concretely, the observer registered the communication process, indicating the speaker, the kind of action (e.g., lecture, question, answer) and the target audience.

In both cases, the processes followed and the unit of analysis is compliant with the proposal presented in this paper. Thus, the envisioned application could have contributed to automatize and simplify the data gathering and integration processes.

5 Conclusions and Future Work

In this paper, we have discussed the importance of observational data inclusion into MMLA dataset. Based on the literature review, we have proposed an approach and an observational data aggregation solution. The suggested approach is an integrated view that answers to challenges such as standards (xAPI), pedagogy (semantics) and data source (real world data). Based on the proof of concept, we envision that the presented approach could be suitable for pedagogy-aware real-world, observational data identification, and it could serve a basis for development of observational data collection solution in a form of classroom observation app.

In our future work, both the approach and the architecture will establish the basis of the conceptual model/design of an app that will support the structured data gathering during the observation process, and enable xAPI compliant data export for its integration with other data sources. Design-based research methodology will be applied using scenario-based participatory design sessions that are aimed to validate the presented approach and the conceptual model of the app.

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IV

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Semantically Annotated Lesson Observation Data in Learning Analytics Datasets: a Reference Model

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Abstract. Learning analytics (LA) and lesson observations are two approaches frequently used to study teaching and learning processes. In both cases, in order to extract meaningful data interpretations, there is a need for contextualization. Previous works propose to enrich LA datasets with observation data and to use the learning design as a framework to guide the data gathering and the later analysis. However, the majority of lesson observation tools collect data that is not compliant with LA datasets. Moreover, the connection between the learning design and the data gathered is not straightforward. This study reflects upon our research-based design towards an LA model for context-aware semantically annotated lesson observations that may be integrated in multimodal LA datasets. Six teachers (out of which 2 were also researchers) with previous experience in lesson observation were engaged in a focus group interview and participatory design session that helped us to evaluate the LA model through the conceptual design of Observata (a lesson observation tool that implements our model). The findings show the feasibility and usefulness of the proposal as well as the potential limitations in terms of adoption.

Keywords: learning design, learning analytics, lesson observations, multimodal learning analytics, semantic annotations

1. Introduction

It has been argued that Learning Analytics (LA) is lacking in understanding the pedagogical context of student activities [1][2][3]. To address this need, articulated learning design can contribute to the interpretation of LA data, creating an actionable feedback loop [4]. In addition, Learning Design (LD) and LA not only enrich each other, but also are important elements for improving teaching and learning: "Learning design provides a semantic structure for analytics, whereas teacher inquiry defines meaningful questions to analyse" [5]. In other words, synergies between LA and LD can be used to support teacher inquiry, reflection and pedagogically grounded learning analytics practice.

Learning Analytics is a field that studies learners and their contexts [6] mainly based on the data coming from digital realms to understand the computer-mediated contexts. However, in order to analyse learning as a whole and understand the context, there is a need for combining data coming from both the physical and digital spaces [7]. Thus, multimodal data collection and analysis techniques –Multimodal Learning Analytics - that go beyond the digital environments can bring novel methods and evidence to understand the teaching and learning processes [8].

New data collection and sensing technologies make it possible to capture human activity (e.g., with wearable cameras, eye and position trackers, or biosensors). Nevertheless, human activity can be tracked not only by automatic digital means or sensors, but also by human labelling. In this article, we argue that lesson observation is a relevant data source that can be semantically described and integrated into LA datasets. However, to the best of our knowledge, lesson observation tools are not compliant with LA datasets [9].

To enable the integration of observations into LA datasets, we propose an LA model for semantically annotated lesson observations. Among the multiple purposes that lesson observation may have, this model focuses mainly on activity tracking. By means of predefined vocabularies extracted from the learning design, this model systematically contextualizes the observations. Besides, this model takes into consideration current LA practices to promote the data integration (i.e., using widely adopted specifications such as xAPI[1]).

This paper presents the research-based design process [10] followed towards the definition of our reference model for LA compliant lesson observations. The proposal is evaluated through the conceptual design of Observata, a lesson observation tool that implements our model. The design process took place in a scenario-based participatory design session using semi-structured, guided focus group interviews with 6 teachers (out of which 2 were also researchers) with previous experience in lesson observation. Such participatory design contributed to the refinement of our model and the identification of limitations to be overcome in our future work.

2. Background and related work

Educational practice, research and development require contextualised data and pedagogically grounded analysis to understand teaching and learning processes [1][2][9]. Indeed, a core challenge for the learning analytics community is to determine conceptual and practical frameworks that can link teachers' intentions with the data retrieved while teaching and learning [1]. Such contextualization may be driven by the learning design, since it reflects the pedagogical intentions in a particular learning context [2] [11] [12].

During recent years, it became obvious that collecting and analysing only digital traces is not enough [3] and that the inclusion of qualitative data into the equation might be beneficial [13]; alternative data gathering techniques could contribute to enriching the digital traces. For example, classroom observations are recommended for understanding an on-going process or situation [14]

Observation is a way of gathering data on individual behaviours, interactions, or the physical setting by watching behaviour, events, artefacts or noting physical

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

characteristics[14]. Methods of lesson observation may be quantitative or qualitative and the data can be collected with different degrees of flexibility (unstructured, semi-structured or structured). Such flexibility relates to the research paradigms and types of data one needs to collect [15][16]. Structured observations (also called systemic) are aimed at collecting quantitative, numeric and systematic data. Quantitative research has small focus, that can be aggregated into variables, while the qualitative focuses on phenomenological complexity of participants' worlds [16]. Researchers may prefer quantitative over qualitative depending on the aims of their research. Among the aforementioned types of observations, (semi)structured observations focused in the interactional setting could be the most similar ones to the digital traces.

Different to what may happen in an interview or in a questionnaire targeting the participants, observations rely on what people do rather than on what people say they did. However, observations have also some limitations such as the susceptibility to the observer bias and the impact that the presence of the observer may have on the context. Besides, observations are time-consuming compared to other data collection methods. If we look at the classroom life, it is so busy that makes it difficult to obtain the detailed account of it [15]. It may contain around 1000 thousand exchanges (or activities) in a single day [17]. For this reason, most of the teaching goes unobserved, even if it is informative to look at such practice for teaching inquiry and research purposes [18]. Aware of the need of combining evidence from the physical and the digital context, the research done in the area of multimodal learning analytics (MMLA) is currently addressing this gap, especially by introducing different kinds of sensors in the learning environment [5], and aggregating into multimodal dataset (e.g., using xAPI [7] [19][20]).

Enriching the datasets with observational data could contribute to obtaining a more realistic view of the educational scenario as it brings the user perspective into LA datasets [7]. However, although there are multiple tools that support the observation process (like Kobo Toolbox[2], FieldNotes[3], Ethos[4], Followthehashtag[5] ,Storify[6], VideoAnt[7], or LessonNote[8]), to the best of our knowledge, there is no one that enables the integration of the observations with other LA data sources for later analysis. Indeed, a number of difficulties hinder the generation of LA compliant lesson observation data at data gathering, integration and analysis levels [5]:

- Data gathering: the lack of guidance in classroom observation applications leads to unstructured and pedagogically neutral data that has no consistent format [8].
- Data integration: the problem of limited number of data sources in the LA solutions [3][21][22] mainly due to the heterogeneity of data models, formats and granularity [4].
- Data analysis: it is mostly time consuming and ineffective process to

[2] http://www.kobotoolbox.org
[3] http://fieldnotesapp.info
[4] https://beta2.ethosapp.com
[5] http://www.followthehashtag.com
[6] https://storify.com
[7] https://ant.umn.edu
[8] http://lessonnote.com

manually code the data [8].

Thus, in order to enhance teacher inquiry and research, we propose to enrich existing LA datasets with observational data, and to analyse such datasets within the framework provided by the learning design. The following sections present the research process towards that aim.

3. Methodology

To connect our research goals with the reality of the observers' practice, we are following a design-based research process [23] which entails a tight relationship between researchers and stakeholders. More concretely, our research is inspired by Leinonen version of design-based research: research-based design. Research-based design is an iterative approach that spans through four phases, namely contextual inquiry, participatory design, product design, and production of software as hypothesis [10]. In this paper, we reflect on the contextual inquiry and the first participatory-design session.

The overall research question addressed in this paper is: *How can we integrate lesson observations to generate semantically annotated, context-aware data in multimodal data sets?* To better understand this question, the contextual inquiry and the participatory design sessions tackle the following aspects:

- RQ1: How can we computationally represent observation data to enable the integration in LA datasets?
- RQ2: What are the process, elements, and motivation of different stakeholders and unit of analysis for observational data collection?

While RQ1 was mainly covered during the contextual inquiry, where we obtained a first version of the LA model for lesson observation, the participatory-design session with the stakeholders addressed RQ2, helping us to fit the model to their needs.

The contextual inquiry phase lasted for 3 years and consisted of literature review and a preliminary study about the how to transform observations into LA data from the semantic point of view [7], partly answering RQ1 at the unit of analysis level (see Section 4.2). Later on, the proof-of-concept study on the lesson observation data aggregation into LA datasets allowed us to shape a preliminary reference model [5]. An extended version of this model is presented in Section 4.

Starting from contextual inquiry, all the stages of the research are iterative and, therefore, the phases of research are not distinctly separated [22]. Thus, the contextual inquiry -through the literature review, the proof-of-concept and the first study- has informed the scenario-based participatory research by providing the initial conceptual design of the lesson observation application and the reference model. Then, the conceptual design - through the participatory design session described in Section 5 - informed the contextual inquiry, helping us to revisit initial ideas about the design concept and evaluate the reference model. In future phases, the updated reference model will inform the product design and vice versa.

4. Learning Analytics Model for Lesson Observations

The overall goal of this research is to introduce observational data into LA datasets in order to provide with more holistic view of teaching and learning processes. In this paper, we offer a reference model for learning analytics that includes lesson observations. This model builds on three main approaches: context-aware, pedagogically grounded, and multimodal LA. Figure 1 provides an overview of our model, showing how the relations among these approaches intersect.

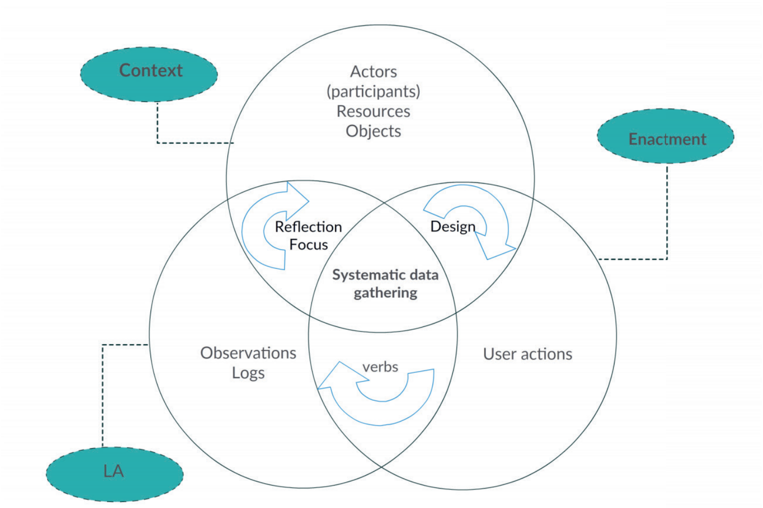

Fig. 1. Learning Analytics Model for Lesson observation

4.1. Theoretical basis

Context awareness. From the perspective of the observation practice, the observer must be aware of the elements of the learning context, i.e., there is a need for context awareness [7]. Similarly, LA researchers state that in order to make sense of the data analysis, there must be a contextualization effort [24]. Thus, in our model we adopt this view of context-awareness, which is aligned with both observation practice and learning analytics.

Pedagogical underpinning. Learning design could be considered a part of the learning context and it also reflects the pedagogical background. Some authors [24] propose the usage of pedagogically grounded LA in order to provide pedagogical meaning to the data analysis. Moreover, others [11] illustrate the benefits of gathering and analysing data, taking into consideration the learning design (e.g., providing more comprehensible and actionable data connected to the teacher concerns). Therefore, in those cases where the design is available, we propose to use this information to guide the observations and the analysis. Following this approach, we expect to: first, bring more evidence to the LA field; and second, create an actionable feedback loop that will help to refine the design and analysis, as well as teaching and learning practice.

Multimodal datasets. The blended nature of technology-enhanced learning and teaching requires gathering evidence from both the digital and the real world [3]. While action logs and the content produced by the participants provide traces of the digital activity, sensors and observations can capture evidence of the real world [25]. Although multimodal datasets normally rely on digital traces and data gathered from sensors [21], our model includes observations in order to incorporate the perceptions and the evidence collected by teachers and observers about the activity of the participants. Thus, in order to enable the data integration with other data sources and the compatibility with different data analysis tools, our model has been designed to be xAPI compliant.

Observation process. Among the different purposes and kinds of observations, our target is to gather evidence about the interactions happening during the teaching and learning processes. Therefore, the envisioned observations will describe participant (inter)actions with other participants or with the context, considering as participants not only teachers and students but also the observers.

From the point of view of the flexibility of making observations, there is a continuum from highly structured to unstructured [16]. On the one hand, highly structured observations restrict the expressiveness in favour of reducing the pre-processing effort. Since, purely quantitative data is criticized for being taken out of context and failing to show the "story of the classroom life" [14], our model answers to this challenge using vocabularies extracted from the context i.e., including all the agents, resources, tools and media involved. These observations are then time-stamped and contextualized on individual, group or community level. On the other hand, unstructured approaches enable observers describe freely an event or interaction, requiring, however, pre-processing (e.g., tagging the observations for their aggregation) before carrying out the analysis. Indeed, some authors argue that classroom observations benefit from qualitative and unstructured approaches [14]. Despite the fact that our model is mainly directed at structured observations (where participant action is registered as a xAPI statement), it also supports unstructured observations (where observations are considered actions carried out by the observer) that later on may be used for better understanding the interactions during the analysis.

As mentioned before, multiple efforts have been done so far in terms of context-aware, pedagogically grounded, and multimodal LA. However, when the existing works have tried to integrate observations in their LA, they have accomplished it through ad-hoc solutions lacking of a methodological framework/model. To our view, the observation process in this context consists of the following steps [7]:

- *Step 1.- Be aware of the elements that belong to the learning context*. To facilitate a systematic observation process, all the actors and objects will be extracted in advance from the learning design, so that the observer links the events to the corresponding actors and objects. It should be noted, that in order to support unstructured observations, observers should be considered as potential actors.
- *Step 2.- Define the areas of focus, the indicators to be obtained in order to illuminate such areas and the specific events to be observed* – the application

is loaded with vocabulary to describe the events to be observed, including actions carried out by the actors involved in learning activity and the observers.

- *Step 3.- Collect observable events*. This is done by subject-verb-object structure and xAPI complex format, time stamped and sent to a learning record storage together with the rest of the MMLA dataset.
- *Step 4.- Analyse and interpret the results*. Observations are analysed together with the rest of the complementary data sources according to the focus defined in step 2.

4.2. Model description

Figure 1 shows not only the relations between context-aware, pedagogically grounded, and multimodal LA, it also specifies how they are aligned with the observation process. In order to connect the observations with the learning design (taking into account the actors, resources, activities, objects), we need to define the events to be observed and the specific verbs to be used, and finally, store it in a computational format that enables the integration with other data sources (xAPI).

Contextualizing and connecting observations with LD. The learning scenario is created in advance or directly imported from the learning design. Meta-data is stored (class, grade, teacher etc), observation protocol is defined, and all the actors, resources, learning activities are registered. Also, the classroom layout may be set, registered and is modifiable as the layout changes. Then, the coding happens on the basis of the chosen pedagogical scenario and framework.

Observable events and verbs. In order to observe the events, we define the foci of interest and we make annotations of events. This is done by coding the events in the classroom and producing real-time semantic annotations. *User actions* are coded and recorded by predefined code-sets [verbs] (in some cases, open coding can be used). Different types of taxonomies and levels of taxonomies (for instance, Bloom's) can be applied by defining the level in the annotated event. The events/notes are placed on the timeline. The levels can involve individual, group, whole-class activities.

Storage. It is important to store the data in a computational format that enables the integration with other data sources (xAPI). Semantically annotated lesson observations are integrated in the MMLA data set for the later analysis and visualization.

Unit of analysis. The central concept of our discourse is the unit of analysis. By definition, the unit of analysis answers to the question "who" and "what" and is the entity we want to describe and analyse [26]. This is the *unit* based on what the analysis is made. In the context of learning analytics, we are interested in tracking the interactions and making inferences on those interactions in a context, so the unit of analysis is the whole *activity*. Units of observation can be different from units of analysis and to obtain information on the unit of analysis, we may use different units of observation (also, in case of our data collection, units of observation can be different) [27].

Lesson observations that are aimed at observing and capturing LA compliant learning activities, need a definition of a universal *unit of analysis*, that can capture activities that were planned and implemented by a teacher. This can be done through annotating observable events; it has been suggested that such unit of analysis is an *event* [7]. *Events* create *stories* that are based on enacted learning scenarios. Previous study on the use of eTextbooks in the classrooms was able to annotate lesson observations with the help of LessonNote[9] app and event-like structured xAPI statements [1].

We conceptualize xAPI statements as *unit of analysis* that in the context of lesson observations are [observable] events. This structure can capture events with any given pedagogical scenario/pedagogical intentions and can be later analysed with other sources of data, since they are structured and semantically annotated xAPI statements. To our view, this unit of analysis is suitable because it is neutral to pedagogical scenarios and intentions, it can express any activity through the verb (the verbs are predefined, so are the pedagogical intentions and indicators), it can be analysed with different methods and pedagogical frameworks and it is LA compliant.

Figure 2 shows different dimensions that influence the unit of analysis within the context of our model: educational theory (context), research approach (observations), technology (semantic annotations in xAPI format).

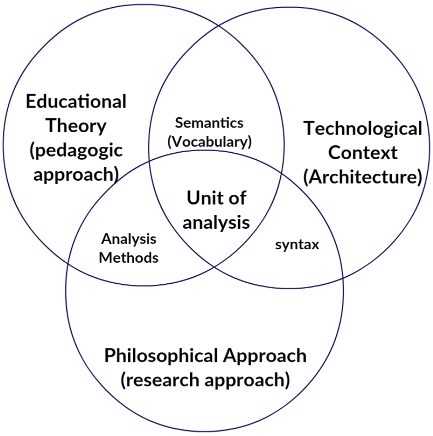

Fig. 2. Different Dimensions of Unit of Analysis

We hypothesize that there can be one neutral *unit of analysis* that can be used to record data with pre-defined teacher intentions, indicators and objectives, define the foci of interest and through semantically annotated observations link it to classroom practice for analysis with MMLA datasets.

[9] http://lessonnote.com/

5. Participatory design

5.1. Description of the study

The overall aim of the participatory study was to evaluate the reference model through the conceptual design of the application. For the design session, we have followed a scenario-based research method, modelling five personas[10] [28] based on the stakeholder profiles representing primary and secondary users of the application (see Table 1). A supervisor teacher represents a primary persona. Secondary personas are: an intern teacher (teacher in training), a head of an educational technology start-up, a teacher-researcher (in-service teacher partnering with the university), and university researcher. The persona models were data-driven [29] and their modelling followed by scenario-development was also iterative and comparative – repeatedly going back and forth from personas to scenarios. Since the final goal of the design session was to validate the model, the scenarios (see Table 2) described hypothetical uses and detailed functionalities of Observata, an application envisioned to implement the proposed LA model for lesson observation. For the study, we chose 6 participants familiarised with the personas described above and with previous expertise in classroom observations. All of them were in-service teachers (4 from secondary and 2 from higher education). Besides, 2 of them had a dual profile being not only teachers but also researchers.

Table 1 Description of personas

Type	Name	Goal	Requirements
Primary	Supervisor teacher	Observe and share observations	Efficiency and easiness of use
Secondary	Intern teacher	Compare the teaching execution vs intentions	Quick and effective annotations
Secondary	Edu Tech start-up head	Track the technology usage in the classroom	Ability to record activities that are using a certain tool
Secondary	Researcher teacher	Understand how pedagogical intentions are implemented (for regulation and reflection	Register, analyse, and visualize activities compare with the intentions
Secondary	TEL researcher	Automatically collect and code data with different semantics	Connect structured and consistent data with other sources

The scenarios introduced in Table 2 describe the hypothetical uses of the lesson observation application, together with specific functionalities that enable collection of LA compliant lesson observation data. While the first scenario represents a simple lesson observation case (independent of the learning design), the second one illustrates the added value of connecting the observations with a specific learning design and context. Then, third and fourth scenarios aim to exploit the benefits of a

[10] Modelled personas http://bit.ly/2skvTd2

context where other LA traces can be gathered for later integration and analysis. The former is shaped to the interests of a head of a TEL start-up, and the later to a teacher with research background.

Table 2 Overview of the scenarios discussed during the participatory design.

Scenario	Personas involved	Process
1. Simple lesson observation case (without lePlanner)	Teacher in training [Supervisor]	1. Manual context description and protocol definition 2. Classroom observation and evidence gathering 3. Observation sharing 4. Discussion
2. Observation based on LePlanner scenario	Supervisor [Teacher in training]	1. Reusing context description 2. Load existing design 3. Protocol definition 4. Classroom observation and evidence gathering 5. Comparison visualization 6. Discussion
3. Observation of a technology-rich lesson	Edu Tech start-up head [Researcher teacher]	1. Manual context description 2. Protocol definition 3. Classroom observations and evidence gathering with several foci of interest (several codesets) 4. Combining two data sources 5. Research
4. Curriculum research based on data observation	Researcher teacher [Edu Tech start-up head]	1. Reusing context 2. Discussion and comparison of semi-automated observation transcript with hand-written annotations using video-recording 3. Data export for analysis 4. Research

For the research based-design, where the researcher is not an objective observer but also a participant, we have used semi-structured, guided interviews and had the session recorded on the audio. Participants were handed-out 4 typical use cases (scenarios)[11], which are summarised in Table 2. The participants, after reading the scenario (each scenario was reviewed by all the participants at the same time), were asked to reflect on it based on specific questions listed in the scenarios. During the guided interviews, where needed, clarifications on the tool functionalities or the model were given. The questions explored during the session were related to our research questions but were semi-structured in order to obtain: general feedback on the feasibility and usefulness, recommendations/modifications suggested from, the usual process and use cases of observations (scenarios with questions are given in the detailed scenarios link in the footnotes).

[11] Detailed scenarios http://bit.ly/2rZxDra

The session was recorded for later thematic analysis with open coding. First of all, before coding we created a preliminary conceptual model based on our reference model, based on the contextual inquiry and scenarios that we have offered to the participants. The themes that emerged already from those scenarios, followed an iterative and comparative process, using inductive and deductive reasoning [30]. This approach helped us validate existing themes and categories and find emerging ones, thus evaluating and redefining the model presented in section 3. In the end, we used axial coding to structure and report our data.

5.2. Conceptual Design of Observata

In order to answer RQ2 and evaluate the conceptual model from engineering and epistemological perspective [31], we have developed a conceptual design of Observata through a contextual inquiry phase. Observata is envisioned as a lesson observation application for tablet computers devoted to collect data according to our reference model.

To enable the integration with the learning context and design, the envisioned tool will allow users to import the scenario from an authoring tool or to create it on the spot (with activities, actors, objects, tools and layout). Out of multiple authoring tools, we have chosen LePlanner[12][32] to integrate our observation tool. This on-line tool managed by Tallinn University is compliant with our reference model and semantics can be easily retrieved based on the scenarios developed by it, or by creating it in the Observata directly. Observata and LePlanner will share the same user accounts, allowing Observata users to view and use learning scenarios from LePlanner as a basis for annotating a lesson observation. Yet, Observata could also be used as a stand-alone tool, without any learning scenario required for lesson observation.

Lesson scenario in LePlanner (Figure 3) contains a set of in-class (blue) or off-class (green) learning activities arranged sequentially on the timeline, along with related learning resources, linked to learning outcomes and marked with an indicator from a pre-defined taxonomy. For instance, in the Figure 3, the width of the learning activities represents their duration, and the length of the bar below timeline indicates the co-authorship level of the learner on the 7-point scale [33] (0 - consuming content, 1 - annotating, 2 - interacting with content, 3 - commenting, 4 - expanding, 5 - remixing, 6 - creating). Code-sets for observations are predefined (partly by the LePlanner scenario) and compliant with the syntax of xAPI statements. Observer can also create theory-driven code-sets, e.g. levels of educational outcomes from Bloom's taxonomy or modes of presence from Communities of Inquiry framework. In addition to predefined code-sets, a user can also use ad hoc codes (folksonomical tags). Thus, the envisioned application allows for structured and unstructured observations (open coding through note taking by adding an observer as an actor, defining verb and object) and semi-structured observations by vocabulary expansion based on codes created on the fly. The observer can use several code-sets in parallel, at the same time. There are several stakeholders that implement observations in different ways but the data is always consistent with context and enacted practice. Observation transcripts

[12] https://leplanner.net

that can be compared to each other and edited using a video transcript. Finally, xAPI compliant data can be exported to Learning Record Store to be combined with other MMLA data sources.

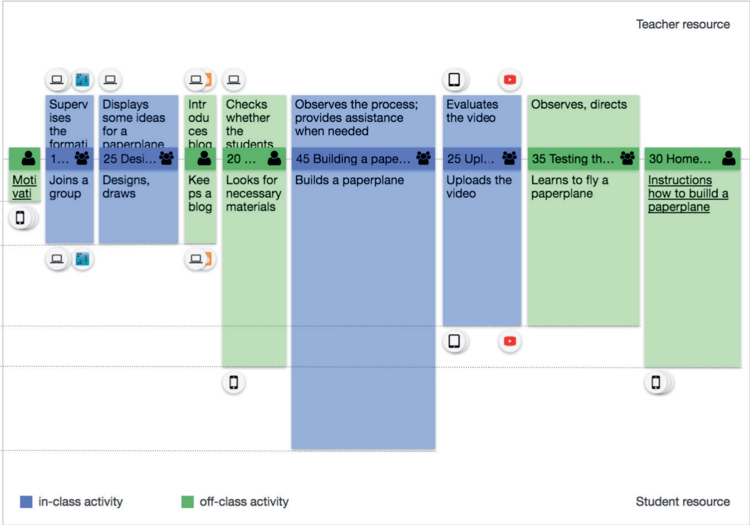

Fig. 3. LePlanner learning scenario creation and sharing tool (learning scenario timeline view)

5.3. Findings

The findings of the participatory design session helped us refine our LA model for lesson observation (RQ1) and better understand the process, elements, motivation of different stakeholders (RQ2). In general, most of the themes/concepts have been validated and accepted by the participants. Regarding the representation of observation data to enable the integration in LA datasets (RQ1), we found out that the most accepted idea was the predefined verbs (code-sets) – the idea was further developed into using several types of predefined code-sets; this was suggested by participants in order to record different types of foci of interest. Regarding the process, elements and motivation of the stakeholders (RQ2) we understood that process was regarded as feasible and the idea interesting. The motivation and the need for such application exist and the idea is well accepted. The *unit of analysis* for data collection was also regarded as appropriate, realistic and feasible.

Structured feedback below gives a more detailed overview of the findings:

- **Feasibility and interest**. All the participants regarded the prototype and the scenarios as feasible and interesting. Events were perceived as a realistic and appropriate *unit of analysis* for observations. The predefined verbs were regarded as relevant for the easiness and consistency of data collection. Moreover, participants have expressed their interest in the following ways:

"When will this app be ready? It is exciting to wait for that minute to see real examples, how it is planned, observed and recorded".

- **Usefulness of the solution**. Overall, the prototype was perceived as useful. The importance of its use in teacher training was highlighted, because observing others' lessons is the part of the teacher training. It was regarded as an effective scaffolding solution. The idea of testing a learning tool in an authentic setting and have the data on its usage was perceived as very promising. Since observations usually are done not in a structured way, predefining the observation protocol and verbs make the approach more systematic. In addition, the idea of comparing enacted practice with teacher intentions (learning design) using several observation transcripts (enacted practice) was well appreciated. Indeed, comparison of the transcripts was regarded as a common practice, and it was suggested to use learning analytics to compare the transcripts, so this part of our model was reinforced. Finally, combining observation data with MMLA datasets (data coming from a tool used in the lesson) was one of the most interesting ideas for the teachers.
- **Recommendations about the observation process**. Regarding the observation process, the participants made several remarks. In terms of data gathering, the use of predefined vocabularies was understood and accepted as a prerequisite to combine observations with other LA datasets. In addition, the participants highlighted their interest in predefining several code-sets, attending the different observation foci. For example, several elements of the lesson observation for students were stressed as important. According to the participants, there must be certain foci predefined (such as work planned, tasks, tools used, or the social level of the activities) and observed (e.g., emotions, motivation, environmental metrics, …) in order to connect the observations and the analysis with the learning context.
  Regarding the following phases of the observation, the participants stressed the importance of reflection and comparison between the learning scenario and observation transcript (e.g., documenting the time difference between the planned and the enacted), and recommended the usage of student feedback to enrich the MMLA dataset.
- **Instrumental/app recommendations**. The participants highlighted the need for reusing the protocols (learning scenario), storing transcripts (contextualized learning scenario) and contextualizing later analysis. Since sharing the transcripts was considered by the participants as a potential scenario, it will be necessary to preserve the privacy of the transcript author (observer) and the anonymity of the participants in the learning scenario.
- **Limitations for adoption**. In terms of data gathering, despite the fact that participants acknowledge the need of predefined and agreed vocabularies to ensure that other observers or LA tools are able to interpret the observations, they reinforced the importance of open coding. Also, they have underlined the importance of a shared and agreed meaning of ad-hoc added codes (which is also relevant for the LA purposes).
  Due to the time constraints during the learning activity, it may be difficult to register observation especially in those cases where the teachers themselves make the observations. To solve this problem, it was suggested to revise and

post-edit the transcript. An interesting idea coming from the participants was to videotape the whole process to have a reliable overview of the sessions. This approach could help to synchronize the observation events with other LA data sources. However, videotaping the session would also require special attention to ethics and privacy issues.

Last but not least, the participants raised their concern about the complexity of the proposal - “It will require a lot of training for teachers to adopt this innovation”.

The participatory design session allowed us not only to address the research questions but also to elicit a number of functionalities required by the users, contributing to the basis of the first tool prototype. Most of the functionalities presented in the usage scenarios have been validated and some were added. Both the model and the participants’ recommendations (methodological and instrumental) have been translated into the first mockups of Observata which is currently under development.

6. Discussion

The findings show that the participants, who represent the main stakeholders of the model and the lesson observation application, have evaluated and accepted the reference model. The findings made it possible to refine the model, and include the methodological and instrumental changes that were posed by the participants and discussed with the researchers. Thus, as a result of the participatory design, we obtained a validated conceptual design of Observata and a refined LA model for lesson observations.

The sub question RQ2 was answered by the participatory design that helped us understand the process, elements, and motivation of different stakeholders. We have defined, explored and validated the process, elements, motivations and *unit of analysis* for observation data collection. We have included the recommendations and suggestions coming from the stakeholders and redefined the app conceptual design and the reference model behind it. The sub-question RQ1 is answered by the fact that the reference model was regarded viable and it was refined: through the use of Observata tool we can identify, code and combine LA-compliant observation data.

Despite of the positive feedback, it is understandable why participants foresee that adopting this kind of solutions may require “a lot of training”: it entails the adoption of the different elements involved in the proposal (LD, LA and MMLA); and the teacher/observer workload is already high before, during and after the observed sessions by default. Nevertheless, we envision that, through user-involvement in the implementation of Observata, we may alleviate those concerns.

Regarding the model, a number of limitations have been detected at the practical and conceptual level. To enable the integration in MMLA datasets, the vocabularies and identifiers should be shared and agreed with the different data gathering sources and analysis tools. However, the observers’ need for open coding approaches (where they can add ad-hoc verbs) restricts the affordances for analysis. Another practical limitation is caused by the time constraints. Observations require time to process and register what is happening in the learning context. Thus, since events registered via observations cannot be timestamped with the same accuracy than other computer-mediated data gathering techniques (e.g., logs), there is a synchronization problem. Moreover, regarding the applicability of our LA model for lesson observation, we acknowledge that the connection with the learning design is not always straightforward. First, it implies a computational version of a learning design, which often does not exist. Second, it is necessary to have access to the instantiation of the learning design in the technological setting, in order to use the appropriated identifiers that will be used by the rest of the data gathering mechanisms. In our case, to establish the connection with the learning design, Observata will be implemented to be compliant with an authoring tool (LePlanner). Alternatively, Observata could be also used with technologies such as GLUE!-PS and GLUE!-CAS that enable the design, instantiation and design-aware data gathering from multiple data sources in CSCL scenarios [11]. Nevertheless, it should be noted that for adoption purposes, as envisioned in the first scenario (see Table 2), Observata could be used as a mere observation tool independently of a learning design. In those cases, observers will be able to define or import the required context and vocabularies directly in the tool.

7. Conclusions and Future Work

In this paper, we have discussed the importance of connecting the learning context, the teacher intentions, and the data gathered from multiple sources during the learning activity in order to provide relevant and rich analysis. We have argued that in this respect, lesson observations are relevant source to include into MMLA datasets. To make it feasible, we have presented learning analytics model for lesson observations that guides the data gathering, aggregation and analysis.

To develop the model, we have followed contextual inquiry and participatory design stages of research-based design process. To evaluate and redefine our model, we have used the conceptual design of Observata in a scenario-based participatory design session using focus group. The findings point out the feasibility and usefulness of the approach. Nevertheless, some aspects such as the management of data privacy issues and the concern about the additional workload (in terms of time and potential complexity of the tasks) remains still open and will require special attention in future iterations. Besides, the focus group made explicit certain limitations of the model regarding the nature of the observations and time constraints while coding. Despite the fact that structured observations may be especially convenient to apply quantitative analysis to aggregated data including observations and user activity traces (e.g., for activity tracking), both the literature [15] and the focus group participants highlight the preference for unstructured and open coded or semi-structured observations. Thus, in the future, we will enable the collection of less structured observations via xAPI. With this extension, we expect to enable more qualitative analysis and to promote the contextualization of the quantitative data. Secondly, even if the privacy issues do not represent our direct concern, since our model deals with the data collection, we will add data anonymisation functionality in the app. And also, we address time constraint and data synchronization issues with specific functionalities by introducing post editing of coded events, photo and video capturing (event-oriented, small videos) functionalities.

The reference model and the conceptual design have informed the prototype of Observata. Following the research-based design process, our next step is to develop the stable prototype through iterative process and further refine the reference model. Software will be tested through use cases, user stories and finally, presented as hypothesis. The reference model behind it will be evaluated through field trials and mixed method approaches (quantitative, qualitative, interviews) and MMLA data (Observata semantic annotations and log data). The data will be analysed with specific pedagogical frameworks.

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Lesson Observation Data in Learning Analytics Datasets: Observata

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Abstract. Observational data can be used to illuminate different areas of teaching and learning process and enrich Learning Analytics data. Majority of lesson observation tools provide observational data that is not compliant with LA datasets. The paper presents Observata – a tablet computer application for context-aware semantic annotations of significant events during real time lesson observations. During the demo-session we expect the participants to engage in the discussion and provide feedback on the prototype.

Keywords: Learning Analytics · Classroom observations · Multimodal learning analytics · Learning design · Semantic annotations

1 Introduction and Background

Learning Analytics (LA) is a field that analyzes learners and their contexts mainly utilizing the data coming from digital realms to understand computer-mediated contexts. It has been argued, that multimodal data collection and analysis techniques that go beyond the digital environments can bring novel methods to understand when students solve problems, interact with peers and act in both – digital and physical worlds [1]. In order to analyze learning as a whole and its context, there is additional data needed. This data can be coming from learning scenarios [2, 3] coupled with documenting their enactment [4].

We argue that real-time human semantic labeling can be used to illuminate different areas of teaching and learning process, enrich LA data and be combined into Multimodal LA (MMLA) datasets. To our knowledge, lesson observation tools provide observational data that are not compliant with LA datasets [4]. The proposed solution is the classroom observation application that is able to aggregate semantic annotations and gather context-aware, human-labeled systematic observational data. This approach takes into account pedagogical underpinnings and collects data that is aligned with specific pedagogical intentions and foci.

In this paper we present Observata prototype. The prototype has been validated with design-based research that involved semi-structured focus group interview during a design session with stakeholders.

In order to understand teaching and learning processes, context of the learning experience is highly relevant; for this purpose, data coming from LMS is not

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enough. Moreover, collection and analysis of only digital traces is not sufficient [1] and inclusion of qualitative data into the equation might be beneficial [5]. MMLA data containing observations can offer insights into this issue and help enrich LA with contextual aspects. Aligning Learning Design and LA helps understanding learning behavior and creating actionable feedback loop [6, 7]. Also, linking the generic pedagogical scenarios with contextualized learning scenarios and LA adds more to the evidence [8]. Combining observational data into MMLA datasets has also been proven useful by some studies [9].

As the classroom life is very busy and there can be around 1000 thousand learning interactions (or activities) taking place within a single day, data collection becomes difficult [10, 11]. At the same time, observational data are especially informative [12]. The approaches used in observations may be qualitative or quantitative; quantitative data is criticized for being taken out of context and failing to show the "story of the classroom life" [10]. Systematic classroom observations that are aimed at capturing learning activities need a defined **Unit of Analysis**. It has been suggested that such unit of analysis is an (Learning) *Event* [4] (observable events). Previous study on observations shows that it is possible to annotate lesson events with xAPI statements [13]. Semantically annotated xAPI statements can then be combined with MMLA datasets.

In the next chapter we present observation application Observata that has been validated by scenario-based participatory design-session with participation of 6 persons representing different stakeholder groups, including in-service teachers, their mentors and teacher educators.

2 Observata

The design of the Observata allows for open and axial coding (with pre-defined codesets). Observata can be used as a stand-alone tool or an extension of learning scenario visualisation tool LePlanner[1]. In latter case, Observata initiates a lesson observation protocol based on a learning scenario from LePlanner, including in lesson annotation of pre-defined tools, artefacts, actors, learning goals and related activities. Even when Observata is used as a stand-alone mode, observer can define beforehand the code sets, classroom settings, devices, actors. Several code sets can be used in parallel during the lesson observation and they can contain different semantics. Each significant *event* in the lesson transcript is documented in a style of a xAPI statement, indicating actor, verb, object, result and context (two latter being optional). Once observer saves the *event*, it is automatically timestamped and represented on a timeline view that creates the story of the lesson. When using pre-defined learning scenario, activities can be marked as delayed by dragging them on the timeline. The transcript of the lesson feeds into the dashboard views. It is possible to connect several data sources and create richer real-time analytics that can be used for reflection and analysis. Below the main use cases of Observata are briefly described.

[1] https://beta.leplanner.net/#/.

Annotating with Open Coding. Classroom map is displayed by the app while annotating the lesson observation. To document a bullying incident between two students (K and L), observer taps first on Student K (*Subject*) on the classroom map, then on Student L (*Object*) and types in the *Verb*: ‘bullies’. Optionally, observer may add the photo and also the *Context* for the incident (ongoing whole-class activity). Even in case of open coding, the most typical verbs (e.g. asks, presents, explains) and most typical objects (e.g. question, task, example, solution) can be dragged from the pre-defined code set on the edge of the screen (Fig. 1).

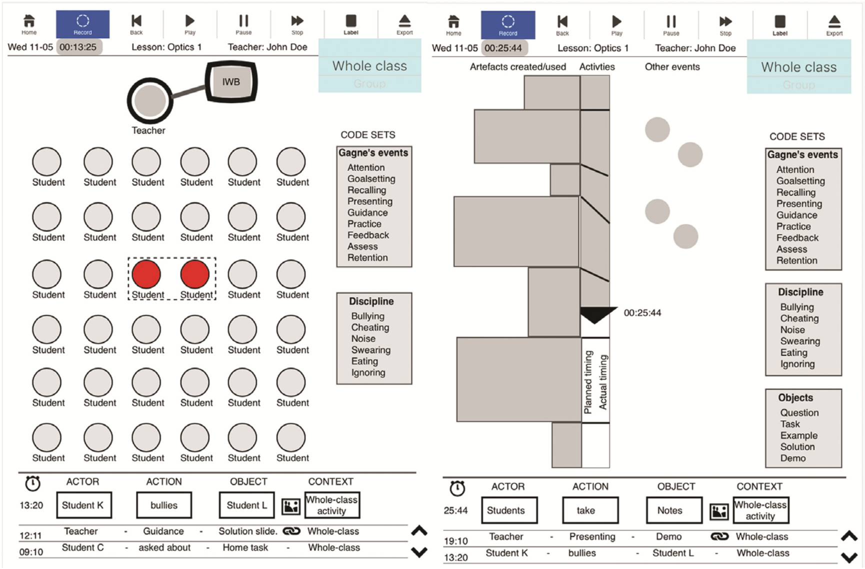

Fig. 1. Classroom (left) and scenario (right) views of the Observata tool

Annotating Using Predefined Code-Sets. To annotate the teacher’s response to student C’s question, the observer taps on *teacher* (*Subject*), then taps on IWB icon and chooses from Code set the *Object* (‘solution’). To select pre-defined *Verb*, observer then drags the label ‘Guidance’ from pre-defined code set based on Gagne’s instructional events.

Annotating the Lesson Based on LePlanner Scenario. To validate the pre-designed lesson plan, observer compares the actual progress of lesson with scenario, noting the delays and disruptions of activities if needed. Subjects, Objects and Verbs are transferred automatically to xAPI statements from LePlanner scenario. However, observer may add additional activities (both parallel and sub-activities).

Analyzing the Lesson Transcript. After finishing the lesson annotation and saving the transcript, observer goes through the transcript together with the teacher and may edit it. Lesson transcripts are visualized on a LA dashboard, but Observata also allows exporting LA data sets to LRS or data analysis software for retrospective analytics, to be combined with data from other sources (e.g. log files).

3 Conclusions and Future Plans

Current prototype of Observata is built for demonstrating and validating the approach to xAPI-driven, real-time annotation of classroom events and related reference model that has been described in detail in our upcoming paper. The stable version of Observata will enter piloting in Tallinn University's initial teacher education programme in the end of year 2017. The piloting will focus on improving user experience of the Observata app, but also on increasing the efficiency, error-proneness and speed of annotations.

The future development of Observata is planned to include additional functionalities, such as code set editor, lesson annotation by two coders simultaneously, and calculation of inter-coder reliability. The latter might be interesting for researchers dealing with classroom ethnography.

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Review

A Conversation between Learning Design and Classroom Observations: A Systematic Literature Review

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Abstract: Learning Design, as a field of research, provides practitioners with guidelines towards more effective teaching and learning. In parallel, observational methods (manual or automated) have been used in the classroom to reflect on and refine teaching and learning, often in combination with other data sources (such as surveys and interviews). Despite the fact that both Learning Design and classroom observation aim to support teaching and learning practices (respectively a priori or a posteriori), they are not often aligned. To better understand the potential synergies between these two strategies, this paper reports on a systematic literature review based on 24 works that connect learning design and classroom observations. The review analyses the purposes of the studies, the stakeholders involved, the methodological aspects of the studies, and how design and observations are connected. This review reveals the need for computer-interpretable documented designs; the lack of reported systematic approaches and technological support to connect the (multimodal) observations with the corresponding learning designs; and, the predominance of human-mediated observations of the physical space, whose applicability and scalability are limited by the human resources available. The adoption of ICT tools to support the design process would contribute to extracting the context of the observations and the pedagogical framework for the analysis. Moreover, extending the traditional manual observations with Multimodal Learning Analytic techniques, would not only reduce the observation burden but also support the systematic data collection, integration, and analysis, especially in semi-structured and structured studies.

Keywords: learning design; multimodal learning analytics; classroom observations; evidence-based practice

1. Introduction

Learning Design or Design for Learning [1], as a field of educational research and practice, aims to improve the effectiveness of learning, e.g., helping teachers to create and make explicit their own designs [2]. A similar term, "learning design", is also used to refer either to the creative process of designing a learning activity or to the artefact resulting from such a process [3]. Despite this emphasis on the creation of learning designs, there is a lack of frameworks to evaluate the implementation of the designs in the classroom [4]. Moreover, in order to evaluate the implementation of learning design, there is a need for evidence coming from those digital or physical spaces where teaching and learning processes take place [5].

Observations (or observational methods) have been traditionally used by researchers and practitioners to support awareness and reflection [6,7]. Especially in educational contexts that occupy, fully or partially, physical spaces, observations offer an insight not easily available through other data sources (e.g., surveys, interviews, or teacher and student journals). Indeed, since human observations are limited to what the eye can see, and are done through the human resources available, automated observations can provide a complementary view and lower effort solution, especially when the learning scenario is supported by technology [8,9]. Thus, the integration of manual and automated observations with other data sources [10] offers a more complete and triangulated picture of the teaching and learning processes [11].

Interestingly, while both learning design (hereafter, LD) and classroom observation (CO) pursue the support of teaching and learning practices, often they are not aligned. To better understand why and how LD and CO have been connected in the existing literature, this paper reports on the results obtained from a systematic literature review. More precisely, this paper explores the nature of the observations, how the researchers establish the relationship between LD and CO and how this link is implemented in practice. Then, the lessons learnt from the literature review led us to spot open issues and future directions that are to be addressed by the research community.

Out of 2793 papers obtained from different well-known databases in the area of technology-enhanced learning, 24 articles were finally considered for the review. In the following sections, we introduce related works that motivated this study, describe the research methodology followed during the review process, and finally, discuss the results obtained in relation to the research questions that guided the study.

2. Supporting Teaching Practice through Learning Design and Classroom Observation

While Learning Design refers to the field of educational research and practice, different connotations are linked to the term 'learning design' (without capitals) [5,12–14]. According to some authors, learning design (LD) can be seen as a product or an artefact that describes the sequence of teaching and learning activities [5,15–17], including the actors' roles, activities, and environments as well as the relations between them [18]. At the same time, learning design is also referred to as the process of designing a learning activity and or creating the artefacts that describe the learning activity [1,13,19]. In this paper, we will reflect not only on the *artefact* but also on the *process of designing* for learning, trying to clarify which one, and how, it is connected with classroom observations.

While designing for learning, practitioners develop hypotheses about the teaching and learning process [20]. The collection of evidence during the enactment to test these hypotheses contributes to the orchestration tasks (e.g., by detecting deviations from the teacher's expectations that may require regulation) to the teacher professional development (leading to the better understanding and refinement of the teaching and learning practices) [16,21] and to the decision making at the institutional level (e.g., in order to measure the impact of their designs and react upon them) [22]. However, the support available for teachers for design evaluation is still low [4] and, as Ertmer et al. note, scarce research is devoted to evaluating the designs [23].

In a parallel effort to support teaching and learning, classroom observation (CO) contributes to refining and reflecting on those practices. CO is a "non-judgmental description of classroom events that can be analysed and given interpretation" [24]. Through observations, we can gather data on individual behaviours, interactions, or the educational setting both in physical and digital spaces [8,25] using multiple machine- and human-driven data collection techniques (such as surveys, interviews, activity tracking, teaching and learning content repositories, or classroom and wearable sensors). Indeed, Multimodal Learning Analytics (MMLA) solutions can be seen as "modern" observational approaches suitable for physical and digital spaces [26], to infer climate in the classroom [27], or to observe technology-enhanced learning [28] or to put in evidence the human and machine-generated data for the design of LA systems [29].

According to the observational methods, the design of the observation should be aligned with the planned activities [30], which, in the case of the classroom observations, are described in the learning design. Later, observers must be aware of the context where the teaching and learning processes take place including, among others, the subjects and objects involved. Again, this need for context awareness can be satisfied with the details provided in the LD artefacts [31]. Finally, going one step further, the context and the design decisions may guide the analysis of the observations [6,32].

Another main aspect of the observations is the protocol guiding the data collection. Unstructured protocols provide observers with full expressivity to describe what they see, with the risk of producing big volumes of unstructured data that is more difficult and time-consuming to interpret [33]. On the contrary, structured observations are less expressive but, on the other hand, are more prone to automatization with context-aware technological means, reduce the observation effort and tend to be more accurate in systematic data gathering [34]; this factor allows for more efficient data processing [35] and makes the integration with other sources in multimodal datasets easier, thus enabling data triangulation [36].

From the (automatic) data gathering and analysis perspective, LD artefacts have been used in the area of LA to contextualise the analysis [37,38] and LD processes to customise such solutions [39]. Symmetrically, both the field of Learning Design and the practitioners also benefit from this symbiosis [5], e.g., by analysing the design process or assessing the impact of the artefacts on learning, new theories can be extracted. Thus, classroom observations (beyond the mere data gathering and analysis technique) could profit from similar synergies with LD processes and artefacts, as some authors have already pointed out [23].

3. Research Questions and Methodology

In order to better understand how learning design and classroom observation have been connected in the existing literature, we carried out a systematic literature review [40] to answer the following research questions:

- RQ1: What is the nature of the observations (e.g., stakeholders, unit of analysis, observation types, when the coding is done, research design, complementary sources for data triangulation, limitations of observations and technological support)?
- RQ2: What are the purposes of the studies connecting learning design and classroom observations?
- RQ3: What is the relationship between learning design and classroom observations established at the methodological, practical and technical levels?
- RQ4: What are the important open issues and future lines of work?

While the first three research questions are aimed at being descriptive and mapping the existing reality based on the research and theoretical works, the last research question was aimed at being prescriptive; by identifying the gaps in literature based on corresponding limitations and research results, we offer future research directions.

To answer these research questions, we selected six main academic databases in Technology Enhanced Learning: *IEEE Xplore, Scopus, AISEL, Wiley, ACM, and ScienceDirect*. Additionally, *Google Scholar* (top 100 papers out of 15500 hits) was added in order to detect "grey literature" not indexed in most common literature databases but potentially relevant to assess the state of a research field.

After taking into account alternative spellings, the resulting query was: ("classroom observation*" OR "lesson observation*" OR "observational method*") AND ("learning design" OR "design for learning" OR "lesson plan" OR "instructional design" OR scripting). Aside from this, the first part of the query was decided based on different possible uses of the term "observation", whereas in the part of the query "learning design" or "design for learning" there are established differences in the use of these related concepts [19] as already discussed in the previous section. At the same time, "instructional design", although it has a different origin, sometimes is used interchangeably [3] and "scripting" [36] are also widely used.

The query was run on 15 March 2018. To select the suitable papers we followed the *PRISMA statement* [41]—guideline and process used for rigorous systematic literature reviews. Although several papers contained these keywords in the body of the paper, we narrowed the search down to title, abstract, and keywords, aiming for those papers where these terms could have a more significant role in the contribution. Therefore, whenever the research engine allowed it, the query was applied to title, abstract, and keyword, obtaining a total of 2793 items from the different databases. After the duplicates were removed, we ended up with 2392 papers. Then, to apply the same criteria to all papers, we conducted a manual secondary title/abstract/keyword filtering, obtaining 81 publications. Finally, abstracts and full papers were reviewed, excluding those that were not relevant for our research purpose (i.e., no direct link between LD and observations—43), not accessible (the paper could not be found on the internet nor provided by the authors—14 papers). Finally, 24 papers were selected for in-depth analysis.

The analysis of the articles was guided by the research questions listed previously. According to the content analysis method [42], we applied inductive reasoning followed by iterative deductive analysis. While the codes in some categories were predefined, others emerged during the analysis (e.g., when identifying complementary data-sources, or when eliciting the influence that LD has on CO and vice versa). As a result, the articles were fully read and (re)coded through three iterations. Figure 1 provides an overview of the codification scheme, showing the categories, the relations and whether the codes were predefined (using normal font) or emerged during the process (in italics).

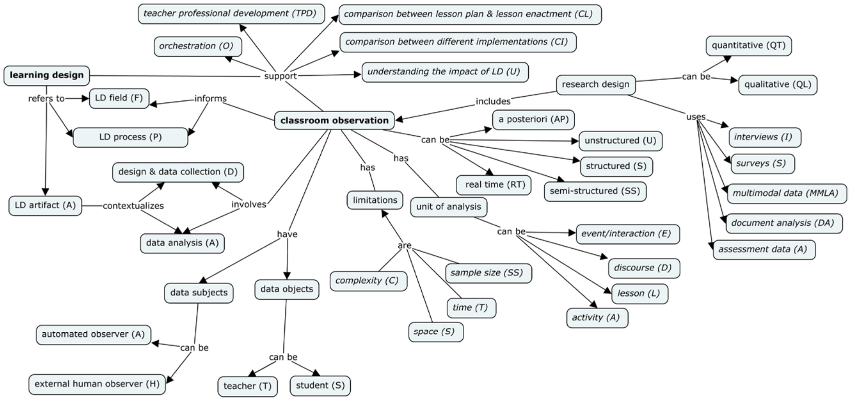

Figure 1. Topics analysed during the paper review and corresponding categories. In bold, central concepts of the analysis. Normal font indicates predefined codes derived deductively. In italics, emerging codes derived inductively.

It should be noted that both predefined and emerging codes were agreed on between the researchers. Although a single researcher did the coding, the second author was involved in ambiguous cases. In most of the cases, the content analysis only required identifying the topics and categories depicted in Figure 1. However, in some cases, it was necessary to infer the categories such as the *unit of analysis*, which had to be identified, based on the research methodology information (further details are provided in the following section).

4. Results and Findings

Table 1 shows the main results of our analysis, including the codification assigned per article. While the main goal was to identify empirical works, we also included theoretical papers in the analysis since they could provide relevant input for the research questions. More concretely, out of 24 papers, we identified 3 papers without empirical evidence: Adams et al provide guidelines for the classroom observation at scale and the other two papers by Eradze and Laanpere, Eradze et al, 2017 reflect on the connections between classroom observations and learning analytics. This section summarises the findings of the systematic review, organised along with our four research questions.

Table 1. Overview of the reviewed papers.

Reference	Data Subjects	Data Objects	Unit of Analysis	Observation Type	Coding Time	Complementary Sources	Design of the Study	Aim of the Study/Paper	LD Guides CO	CO Informs LD	Limitations of the Observations
Adams et al, 2012 [43]	H	T, S	A	S	RT	I, DA	QT	TPD	D	A	NA
Anderson, 2015 [44]	H	NA	E	NA	NA	DA	NA	TPD	D, A	A	NA
Eradze & Laanpere, 2017 [45]	H, A	T, S	E	SS, S, U	RT	–	QT, QL	TPD, O, CI, CL, U	D, A	P, A	T, C
Eradze et al, 2017 [46]	H, A	T, S	E	SS, S, U	RT	–	QT, QL	TPD, O, CI, CL, U	D, A	P, A	NA
Freedman et al, 2012 [47]	H	T, S	NA	SS	AP	I	QL	O, U	A	P	NA
Ghazali et al, 2010 [48]	H	T, S	A, E	U	AP	I, DA	QL	TPD, U	D	F	NA
Hernandez et al, 2015 [49]	H	T, S	A, E	SS	RT	DA, A	QL	O	D, A	A	NA
Jacobs et al, 2008 [50]	H	T, S	L	S	RT	S, DA	QT	TPD	D	P	SS
Jacobson et al, 1991 [51]	H	T	NA	S	RT	I	QT	TPD	D	P	NA
Kermen, 2015 [52]	H	T, S	A	U	AP	I, DA	QL	O, U, TPD	D	P	NA
Molla & Lee, 2012 [53]	H	T, S	E, A	S	RT	I, DA	QT, QL	CI, CL	D, A	A	NA
Nichols, 2007 [54]	H	T, S	E	S	RT	I, DA, A	QT	U, TPD	D, A	P	NA
Phaikhumnam & Yuenyong, 2018 [55]	H	T, S	NA	U	AP	DA, A	QT, QL	O, TPD	D, A	A	NA
Procter, 2004 [56]	H	T, S	A	S	RT	I	QT, QL	O	D	P	SS
Ratnaningsih, 2007 [57]	H	T, S	A	SS	AP	I, DA	QL	CL	A	P	NA
Rozario et al, 2016 [58]	H	T, S	A, E	SS	AP	I, DA	QL	O	D	P	NA
Simwa & Modiba, 2015 [59]	H	T, S	E	SS	AP	I, DA	QL	CL, TPD	D, A	P	NA
Sibanda, 2010 [60]	H	T, S	E	U	AP	I, DA, S	QT, QL	U	A	A	T
Suherdi, 2017 [61]	H	T, S	A	SS	AP	I, DA	QT, QL	CL, U	D, A	P	S
Solomon, 1971 [62]	H	T, S	E	SS	AP	NA	QL	CL, O	D, A	F	T
Suppa, 2015 [63]	H	T, S	NA	S	RT	I, DA, A, S	QT	O	D	P	T, SS
Vantassel-baska et al, 2003 [64]	H	T, S	E	S	RT	NA	QT	TPD, O	A	P	NA
Varsfeld, 1998 [65]	H	T, S	E	SS	RT	I, DA	QT, QL	U, CL, TPD	A	P	NA
Zhang, 2016 [66]	H	T, S	E, D, A	U	AP	DA	QL	U	D	F	NA

Notes: RQ1: Data subjects/data objects (H = external human observer, A = automated observer, T = teacher, S = student, NA = not available); Unit of analysis (A = activity, E = event/interaction, D = discourse, L = lesson, NA = not available); Observation type (S = structured, SS = semi-structured, U = unstructured, NA = not available; Coding time (RT = real time, AP = a posteriori, NA = not available); Complementary sources (S = survey, I = interview, DA = document analysis, A = assessment, NA = not available); Design of the study (QT = quantitative, QL = qualitative, NA = not available); RQ2: Aims of the study/paper (O = orchestration, CI = compare different implementations, CL = compare lesson plan and lesson enactment, U = understand the impact of the LD, TPD = support teacher professional development); RQ3: LD guides CO (D = LD guides the observation design and data collection, A = LD guides the data analysis); CO informs LD (A = recommendations to improve the design artefact, P = recommendations to improve the design process, F = support the theories of the field); RQ4: Limitations: (T = time constraints, S = Space constraints, SS = sample size, C= complexity).

4.1. RQ1—What is the Nature of the Observations?

The distribution of observation roles among data subjects and objects was clear and explicit in every paper. In all cases, external human observers were in charge of the data collection and coding—twice in combination with automated LA solutions (in this case, a proposal to involve LA solutions) [45,46]—with both teachers and students as the common data objects (22 papers). Although the definition of the *unit of analysis* is an important methodological decision in observational studies or research in general [35,67–69] we only found an explicit reference to it in one paper [66]. Nevertheless, looking at the description of the research methodology, we can infer that most of the studies focused on *events* (directed at interaction and behavioural analysis) (14) and *activities* (10).

While either structured or semi-structured observations (10 and 10 respectively) were the most common observation types, unstructured observations were also mentioned (7). Interestingly, just two papers conceived the option of combining the three different observational protocols [45,46]. Going one step further and looking at how the observation took place, there was an equal distribution between real-time and a posteriori cases, but in all cases following traditional data collection (i.e., by a human). The existence of so many a posteriori observational data collection could be closely related to the limited resources and effort often available to carry out manual observations.

A variety of research designs were followed in the studies: 9 papers reported qualitative methods, 6 quantitative and 8 mixed methods. Most of them combined observations with additional data sources, including documents (16), interviews (15), assessment data (4), and surveys (3). In a majority of cases, aside from observations, there were at least two other sources of data used (16 cases).

Most of the papers use (or consider using) additional data sources that were not produced automatically, as happened with the observations. This fact illustrates how demanding data integration of (often multimodal) data can be. While MMLA solutions could be applied in a variety of studies, quantitative and mixed-method studies that enriched event observations with additional data sources—see, e.g., [53,54,60,65] are potential candidates to benefit from MMLA solutions that aid not only the systematic data gathering but also the integration and analysis of multiple data sources.

Regarding the learning designs, the majority of papers included the artefact as a data source where they applied document analysis to extract the design decisions. Moreover, in several studies—e.g., [44,58,59]—the learning design was not available and was inferred a posteriori, with indirect observations. These two situations illustrate one of the main limitations for the alignment with learning design: LDs are not always explicit or, if they are documented, come in different forms (e.g., including texts, graphical representations, or tables) and level of detail tables [70,71]. Apart from being time-consuming, inferring or interpreting the design decisions is error prone and can influence the contextualization. This problem, also mentioned by the LA community when attempting to combine LD and LA [32,72], shows the still low adoption of digital solutions (see for example the Integrated learning design environment (ILDE: http://ilde.upf.edu) that supports the LD process and highlights the need for a framework on how to capture and systematise learning design data.

4.2. RQ2—What are the Purposes of Studies Connecting LD and CO?

According to the papers, the main reasons identified in the studies were: To support teacher professional development (13), classroom orchestration (11), and reflection, e.g., understanding the impact of the learning design (10) or comparing the design and its implementation (8). Moreover, in many cases (13), the authors report connecting LD and CO for two or more purposes at the same time. Therefore, linking LD and CO can be useful to cater to several research aims and teacher needs. The fact that this synergy is mostly used to support teacher professional development can be also explained with the wide use of classroom observations in teacher professional development and teacher training.

4.3. RQ3—What is the Relationship between Learning Design and Classroom Observations Established at the Methodological, Practical and Technical Level?

One of the aims of our study was to identify the theoretical contributions that aim at connecting CO with LD. Only three papers aimed at contributing to linking learning design and classroom observations. Solomon in 1971 was a pioneer in bringing together learning design and classroom observations. In his paper [62] the author suggested a process and a model for connecting CO and LD in order to compare planned learning activities with the actual implementation in the classroom. In his approach, data was collected and analysed based on LD, attending specific foci of interest. It also looks at previous lessons to get indicators on the behavioural changes, and aligns them with the input (strategies in the lesson plan), coding student and teacher actions and learning events by identifying actors (according to objectives in the lesson plan), output (competencies gained in the end). The approach also places importance on the awareness and reflection possibilities of such observations, not only from teachers but also from students. Later on, Eradze et al. proposed a model and a process for lesson observation, which were framed by the learning design. The output of the observation is a collection of the statements represented in a computational format (xAPI) so that they can be interpreted and analysed by learning analytics solutions [45,46]. In these papers, the authors argue that the learning design not only guides the data gathering but also contextualises the data analysis, contributing to a better understanding of the results.

At the practical level, the relation established between learning design and classroom observation was mainly a guidance at different degrees: either the authors reported to have observed aspects related to the learning design (eight papers), or to interpret the results of the observational analysis (six papers) or, from the beginning, the learning design guided the whole observation cycle (i.e., design, data gathering, and analysis) (10 papers). *How is CO reflected on LD and Learning Design as a practice?* In 15 cases, the final result of the synergy was recommendations for teaching and learning practice (design for learning), in eight cases the use of observations aimed at informing the LD, and three papers had used CO to contribute to theory or the field of LD in general. In other words, while many papers used the learning design artefact, the observations contributed to inform the (re)design process.

Additionally, from the *technical perspective*, it should be noted that none of the papers reported having used specific tools to create learning design or to support the observational design, the data collection nor the analysis process. Nevertheless, one paper [45] presented a tool that uses the learning design to support observers in the codification and contextualization of interaction data. The fact that most of the papers have extracted the LD using document analysis indicates low adoption of LD models and design tools by researchers and practitioners. Thus, there is a need for solutions that enable users to create or import the designs that guide the contextualization of the data collection and analysis.

4.4. RQ4—What are the Important Open Issues and Future Lines of Work?

Although most of the papers did not report limitations in connecting LD and CO (18 papers), those who did refer to problems associated with the observation itself such as time constraints (difficulties annotating/coding in the time available [62,63], space constraints - observer mobility [61] and sample size [50,56,63].

Furthermore, as a result of the paper analysis, we have identified different issues to be addressed by the research community to enable the connection between LD and CO, and achieve it in more efficient ways, namely:

4.4.1. Dependence on the Existence of Learning Design

Dependence on the LD as an artefact is one of the issues for the implementation of such a synergy: while in this paper we assume that the learning design is available, in practice, this is not always the case. Often, the lesson plan remains in the head of the practitioner without being registered or formalised [32,72]. Therefore, for those cases, it would be necessary to rely on bottom-up solutions whose goal is to infer the lesson structure from the data gathered in the learning environment [73]. However, solutions of this type are still scarce and prototypical.

4.4.2. Compatibility with Learning Design Tools

The studies reviewed here did not report using any LD or CO tool. However, to aid the connection between learning design and classroom observations, it is necessary to have access to a digital representation of the artefact. Tools such as *WebCollage* (https://analys.gsic.uva.es/webcollage), *LePlanner* (https://beta.leplanner.net) or the *ILDE* (Integrated Learning Design Environment, https://ilde.upf.edu) guide users through the design process. To facilitate compatibility, it would be recommendable to use tools that rely on widespread standards (e.g., IMS-LD – a specification that enables modelling of learning processes) instead of proprietary formats. From the observational side, tools such as *KoboToolbox* (http://analys.kobotoolbox.org), *FieldNotes* (http://fieldnotesapp.info), *Ethos* (https://beta2.ethosapp.com), *Followthehashtag* (http://analys.followthehashtag.com, *Storify* (https://storify.com), *VideoAnt* (https://ant.umn.edu), and *LessonNote* (http://lessonnote.com) have been designed to support observers during the data collection. Also, in this case, for compatibility reasons, it would be preferable to use tools that allow users to export their observations following standards already accepted by the community (e.g., xAPI).

4.4.3. Workload and Multimodal Data Gathering

As we have seen in the reviewed papers, observation processes often require the participation of ad-hoc observers. To alleviate the time and effort that observations entail, technological means could be put in place, enabling teachers to gather data by themselves [74]. For example, (multimodal) learning analytics solutions that monitor user activity and behaviour [26,73,75,76] could be used to automate part of the data collection or to gather complementary information about what is happening in the digital and the physical space. It is also worth noting that the inclusion of new data sources may contribute not only to promoting the quality of analysis (by triangulating the evidence), but also to obtaining a more realistic interpretation of the teaching and learning processes under study.

4.4.4. Underlying Infrastructure

To the best of our knowledge, there is no tool or ecosystem that enables the whole connection between LD and CO (i.e., creation of the learning design, observational design, data gathering, integration, and analysis). From the reviewed literature only one tool, Observata [45,46] could fit this purpose. However, this tool was still under design and therefore not evaluated by the time this review took place.

5. Conclusions

This paper reports a systematic literature review on the connection between learning design and classroom observation, where 24 papers were the subject of analysis. These papers illustrate the added value that the alignment between these two areas may bring, including but not limited to teacher professional development, orchestration, institutional decision-making and educational research in general. To cater to the needs for evidence-based teaching and learning practices, this review contextualises classroom observations within modern data collection approaches and practices.

Despite the reported benefits, the main findings from the papers lead us to conclude that in order to make use of the synergies of linking LD and CO, technological infrastructure plays a crucial role. Starting from the learning design, this information is not explicit and formalising it implies adding extra tasks for the practitioners. Similarly, ad-hoc observers are in charge of data collection and analysis. Taking into account that the *unit of analysis* in most cases is the event (interaction-driven) or the activity, the workload that the observations entail might not be compatible with teaching at the same time, and, therefore, require external support. Nevertheless, despite using multiple data sources in research, none of the papers have reported automatic data gathering or the use of MMLA solutions for its analysis. Thus, to enable inquiry processes where teachers and researchers can manage the whole study, we suggest that MMLA solutions could contribute to reducing the burden by inferring the lesson plan and by automatically gathering parts of the observation.

Moreover, to operationalise the connection between the designs, it will be necessary to promote the usage of standards both in the LD and the CO solutions, so that we can increase the compatibility between platforms. This strategy could contribute to the creation of technological ecosystems that support all the steps necessary to support the connection between the design and the observations. Additionally, there is a need for methodological frameworks and tools that guide the data gathering and integration, so that the learning design is taken into consideration not only to frame the data analysis but also to inform the observational design. Furthermore, this paper mainly illustrates the benefits that LD and CO synergies may bring to researchers focusing on educational research, but more development would be needed for teacher adoption and teaching practice.

Finally, coming back to the research methodology of this paper, our study presents a number of limitations: First, restricting the search to the title, abstract or keywords may have caused the exclusion of valuable contributions; and second, the lack of explicit descriptions or omission about the LD and CO processes/artefacts in the papers may have caused deviations in the codifications. Nevertheless, the analysis of the collected papers still illustrates the synergies and challenges of this promising tandem of learning design and classroom observation.

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VII

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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 sensemaking, 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,

[1] https://leplanner.ee

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

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.

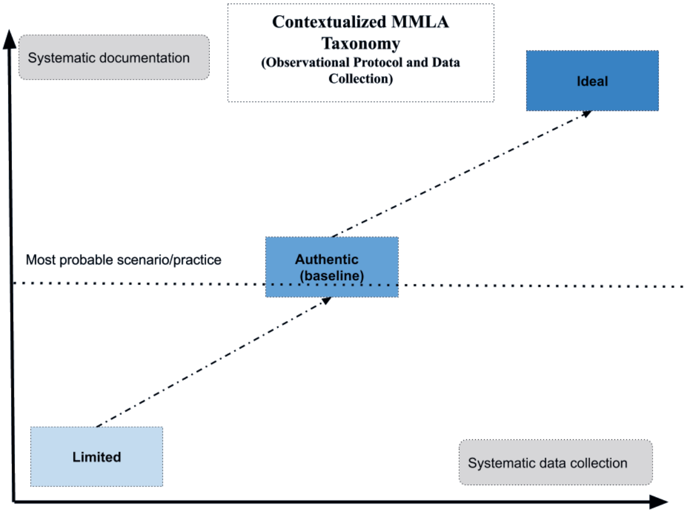

Fig. 1. Context-aware MMLA taxonomy

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 systematically 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

4.1 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.

4.2 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

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

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.

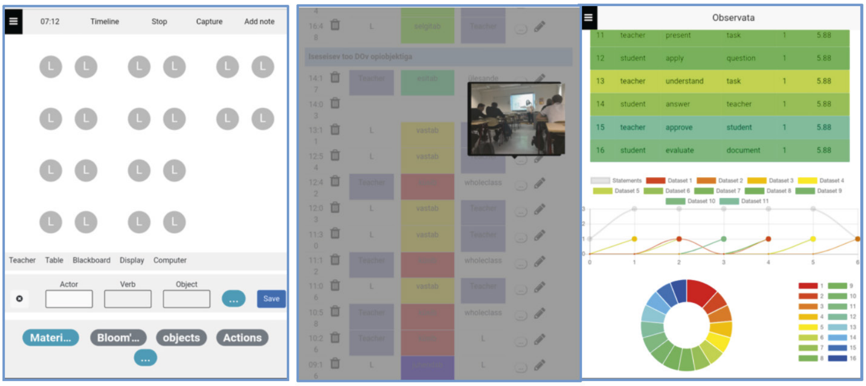

Fig. 2. Observata screens (from left to right): observation view to collect data in xAPI format, data visualised on the timeline, data visualised on the dashboards.

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.

4.3 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 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.

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

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).

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.

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 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. On the other hand, multimodal dataset offered multiple opportunities.

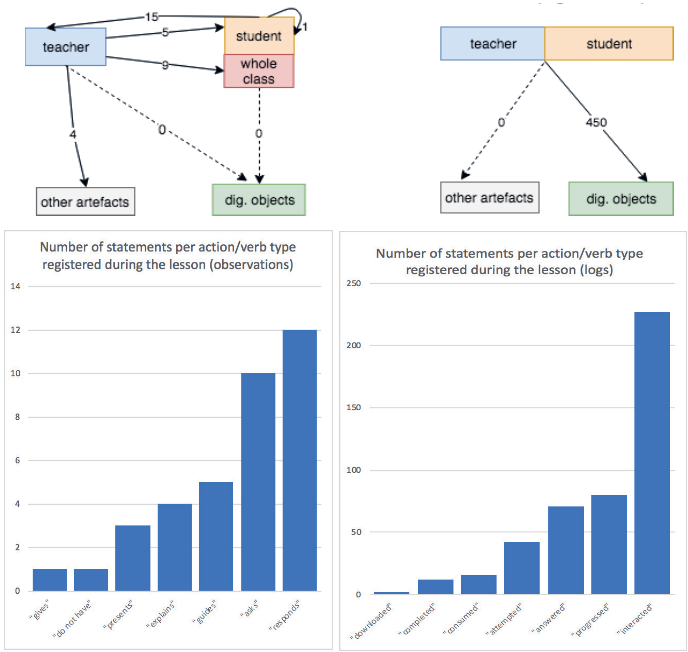

Fig. 3. Upper: Overview of the amount and type of interactions in the physical (left) and in the digital space (right) Down: the frequency of each (inter)action type or verb in observations (physical interactions) and logs (digital interactions). Note the difference in scale of each graph

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 5). 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.

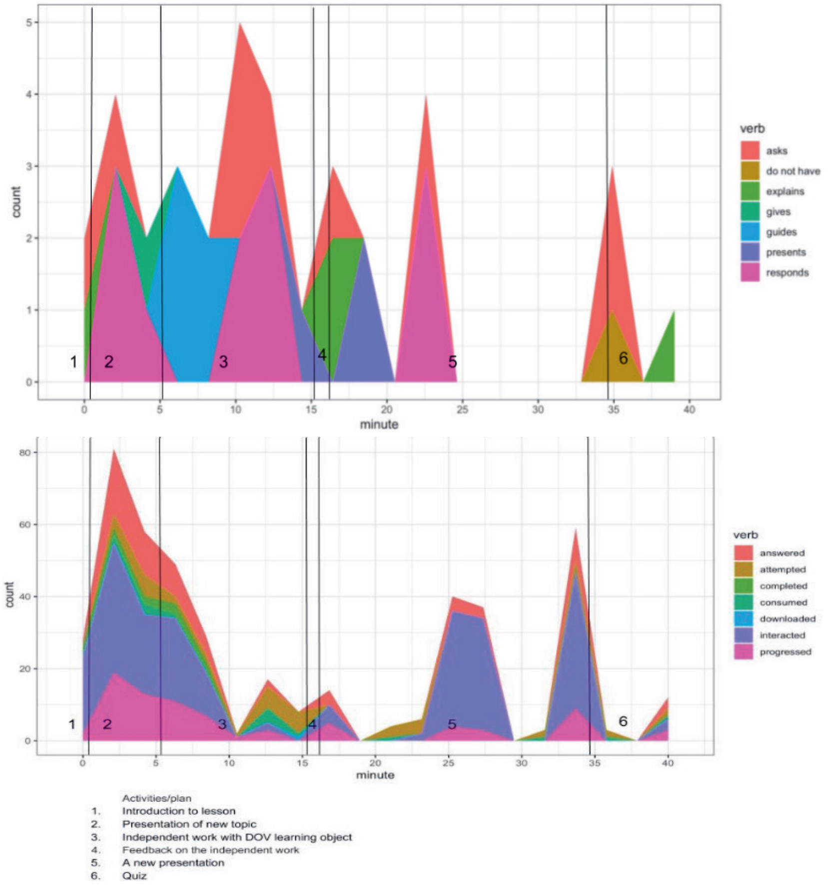

Fig. 4. Timeline representation of the interactions registered in observations (physical interactions - first) and digital traces (digital interactions - second). The vertical lines represent the limits of activities (observed lesson structure) where the interactions took place.

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 not establish the con-

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

nection 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.

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.

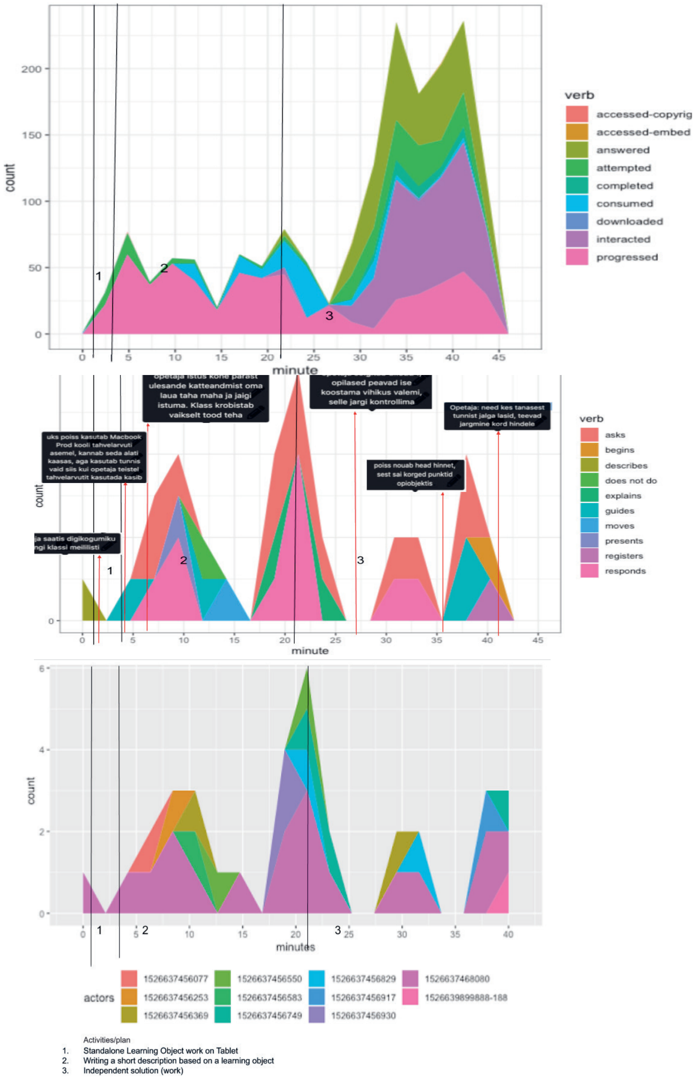

Fig. 6. Examples of visualisations generated during the second iteration: on top - interactions in digital space, in the middle - interactions from physical space with field notes[6] and logs. In the

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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.

bottom - the number of the observed actions per actor, the teacher is dark pink) contextualised in observed lesson structure.[7]

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 finall, 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.

4.4 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.

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

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.

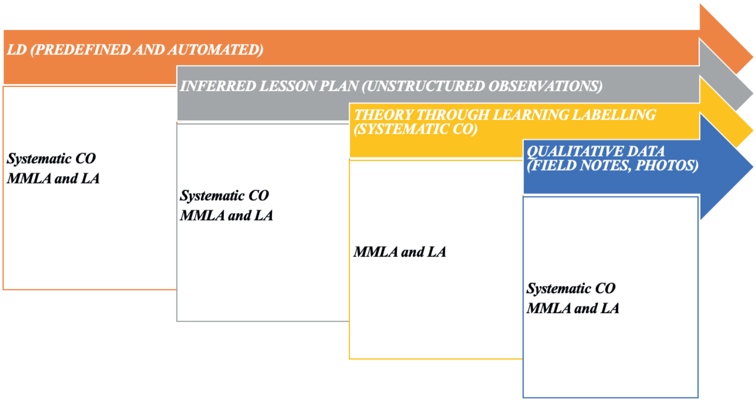

Fig.7. Layered contextualisation levels supported by and afforded by Observata

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".*

KOKKUVÕTE

ÕPIANALÜÜTIKA LAIENDATUD ÕPIRUUMIS: KONTEKSTUALISEERITUD MULTIMODAALSETE TUNNIVAATLUSTE MUDEL

Õppeprotsess ei ole tänapäeval enam piiratud füüsilise klassiruumiga, vaid kandub osaliselt ka virtuaalsesse ruumi. Analüüsimaks terviklikul moel õpisündmusi hübriidses (füüsilis-virtuaalses) ruumis on vaja nende kohta andmeid koguda erinevate vahenditega. Kui osa õppeprotsessi analüüsiks vajalikest andmetest tuleks ka edaspidi koguda traditsioonilisel moel (nt. küsimustike, vaatlusprotokollide, testidega), siis tänapäeval on digikeskkonnas avanemas ka alternatiivsed viisid andmekorjeks.

Õppija interaktsiooni digitaalse õppematerjaliga on põhjalikult erinevatest vaatenurkadest uuritud (Söller et al., 2005). Digitaalsete õpikeskkondade laiaulatuslik kasutuselevõtt on toonud kaasa teadlaste tähelepanu õpianalüütika meetodite arendamisele (Ochoa & Worsley, 2016) ja ka õpianalüütika teadlaste kogukonna kasvule. Kui aga õpianalüütika piirduks vaid ühe konkreetse veebipõhise õpikeskkonna sisse kogunevate interaktsiooniandmetega, siis meenutab see lugu purjus mehest, kes otsib ööpimeduses oma võtmeid mitte sealt, kus ta need kaotas, vaid tänavalaterna juurest - sest seal on ju valgem (Freedman, 2010). Suurem osa õpitegevustest toimub siiski veel väljaspool digiplatvorme ja nendest ei jää maha digitaalset jälge. Taolise "tänavalaterna efekti" vältimiseks on täna kiiresti kasvamas multimodaalse õpianalüütika (MMLA, Multimodal Learning Analytics) instrumentaarium ja sellest huvitatud teadlaste kogukond. Tüüpiliselt kogutakse MMLA andmestik nii füüsilisest kui digikeskkonnast, sealhulgas erinevate mobiilsete andurite abil (Ochoa & Worsley, 2016). Samas vajavad sedalaadi automaatselt kogutud andmed üldjuhul täiendavat märgendamist ja tõlgendamist inimese poolt. Näiteks on anduritelt laekunud andmete pedagoogilise konteksti mõistmiseks kasutatud õppedisaini või õpetaja tunnikava (Lockyer & Dawson, 2011) (Rodríguez-Triana, Martínez-Monés, Asensio-Pérez, & Dimitriadis, 2013). Sageli kasutatakse andurite abil kogutud andmestike analüüsil kvalitatiivsetest uuringudisainidest tuttavat kodeerimist (Worsley et al., 2016)(Di Mitri et al., 2019).

Traditsiooniliselt on füüsilises õpikeskkonnas toimuva õppeprotsessi kohta kogutud andmestikke tunnivaatluste abil, mille puhul vaatleja süstemaatiliselt loob, märgendab ja analüüsib nii kvalitatiivsed kui kvantitatiivsed andmeid (Cohen et al., 2018). Samas pakub vaatlusprotokoll õppeprotsessist üsnagi piiratud ja fragmenteeritud pildi. Vaatlusandmestiku muudavad ebatäiuslikuks nt. protkollimisele kuluv aeg, tunnis toimuvate mikrosündmuste ajaline kattumine (vaatleja ei suuda samaaegselt toimuvaid sündmuseid märgata ja dokumenteerida), vaatleja mõju tunnis toimuvale, makro- ja mikrotegevuste seostamine.

Tunnivaatluste käigus kogutud andmed võiksid oluliselt rikastada MMLA andmestikke ning teisalt võib MMLA abil tunnivaatluste protokollimist kiirendada ja neile täpsust lisada. Seetõttu keskendub käesolev doktoritöö nende kahe lähenemise kombineerimise ja vastastikuse toetamise võimaluste uurimisele. Konkreetsemalt on selle uurimuse eesmärgiks kaardistada tunnivaatluste ja MMLA sünergia digirikastatud klassiruumis toimuva õppetöö analüüsimisel. Õppeprotsessi pedagoogilise konteksti arvestamine on õpianalüütikas seni olnud väljakutseks, käesolev doktoritöö siinkohal lahendusena õpetaja pedagoogilisi kavatsusi väljendava õppedisaini seostamisvõimaluse tunnivaatluse ja MMLA andmetega. Selline eri andmekogumisviiside sünergia võimaldab haridusteadlastel saada senisest terviklikuma pildi tunnis toimuvast õppeprotsessist, rikastades automaatselt kogutud andmestikke tunni kavandaja ja vaatleja poolt mõtestatud pedagoogilise kontekstiga.

Käesolev doktoritöö pakub terviklikuma õpianalüütika jaoks välja nii kontseptuaalse raamistiku kui ka tehnoloogilise vahendi Observata, mis loodi Tallinna Ülikoolis uuringupõhise disaini meetodil (Leinonen et al., 2008). Nii raamistik kui Observata tööriist läbisid mitu arendustsüklit, mille raames neid katsetati lõppkasutajatega. Lisaks süstemaatilisele teaduskirjanduse analüüsile viidi läbi üks kasutajaid kaasav disainisessioon ja kaks juhtumiuuringut, milles osales üle kümne inimese. Loodud kontseptuaalse raamistiku peamisteks osadeks on (a) metodoloogilised alused ja protseduur süsteemsete tunnivaatluste läbiviimiseks ja (b) kontekstitundliku multimodaalse õpianalüütika taksonoomia.

Doktoritöö koosneb seitsmest artiklist, millest kuus on avaldatud ja seitsmes avaldamiseks vastu võetud. Töö koosneb kuuest peatükist, neist esimene pakub sissejuahtava ülevaate uuringu eesmärkidest, protsessist ja väljunditest. Teises peatükis on esitatud töö teoreetilised lähtekohad, kolmandas uurimisprobleem ja -küsimused, neljandas uuringu metodoloogilised alused ja uuringudisain. Viiendas peatükis antakse kokkuvõtlik ülevaade doktoritöö raames avaldatud artiklitest ja nendes saavutatud uurimistulemustest. Viimases peatükis esitatakse uuringu kokkuvõtted ja ettepanekud edasisteks uuringuteks samal suunal.

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2005–2007	Haridustarkvara tõlkija, Hirvehüppe SA, Georgia Haridus- ja Teadusministeerium

Teadustöö põhisuunad

Õpianalüütika, multimodaalne õpianalüütika, tunnivaatlused, õppedisain, tõenduspõhised praktikad hariduses, veebipõhised massikursused, digiõpe

Teadusorganisatsiooniline tegevus

Computer Applications in Engineering Education, teadusajakirja retsensent; EC-TEL (European Conference on Technology-enhanced Learning), programmikomitee liige; ICEM (International Conference of Educational Media), programmikomitee liige; EATEL JTEL doktorantide rahvusvaheline suvekool, korraldustoimkonna liige; TEA (Intl. Conference of Technology-Enhanced Assessment), programmikomitee liige; IRRODL (International Review of Research in Open and Distributed Learning) teadusajakirja retsensent; Educational Sciences Journal teadusajakirja retsent; Educational Data Mining 2017 konverentsi posterettekannete programmikomitee liige; LASI Spain 2017 (Learning Analytics Summer Institute), programmikomitee liige; eLearning Papers teadusajakirja erinumbri "Language Learning and Technology" retsensent; ICWL 2015 (International Conference of Web-based Learning) programmikomitee liige

CURRICULUM VITAE

Name	Maka Eradze
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Citizenship	Georgian

Education

Since 2015	Tallinn University, PhD student at the School of Digital Technologies, Technology-enhanced Learning field
2012–2014	PhD Exchange Erasmus Student, School of Digital Technologies, Tallinn University, Tallinn, Estonia
2003–2005	Tbilisi State University, MA, Byzantine and Modern Greek Studies
1998–2003	Tbilisi State University, BA, Teacher of Modern Greek and Georgian languages

Professional experience

Since 2020	Research Fellow in Technology-enhanced Learning and Learning analytics, University of Modena and Reggio Emilia, Modena, Italy
2018-2020	Researcher in Technology-enhanced Learning, University of Naples Federico II, Naples, Italy
2015–2016	Researcher in Technology-enhanced Learning, University of Naples Federico II, Naples, Italy
2009–2013	eLearning coordinator, consultant for technology-enhanced learning, Tbilisi State University, Tbilisi, Georgia
2010–2012	Teacher network coordinator, consultant for technology-enhanced learning, Partners in Learning Program - Microsoft Georgia, Tbilisi, Georgia
2008–2009	Teacher network coordinator, "Deer Leap Foundation", Ministry of Education and Science of Georgia, Tbilisi, Georgia
2007–2008	Assistant to international relations coordinator, "Rustaveli Scientific Foundation", Ministry of Education and Science of Georgia, Tbilisi, Georgia
2005–2007	Translator (localization) of Educational Software, "Deer Leap Foundation", Ministry of Education and Science of Georgia, Tbilisi, Georgia

Scientific interests

Learning analytics, multimodal learning analytics, classroom observations, learning design, evidence-based educational practices, massive online open courses, blended learning

Academic service

Computer Applications in Engineering Education, reviewer; EC-TEL - European Conference on Technology-enhanced learning, program committee, International Council of Educational Media (ICEM2018), program committee; EATEL JTEL Summer School in Technology-Enhanced Learning, the organisation committee; TEA Conference, program board member; International Review of Research in Open and Distributed Learning (IRRODL) reviewer; Educational Sciences Journal, reviewer; Educational Data Mining Conference 2017, poster track program board member; Learning Analytics Summer Institute Spain 2017, program board member; eLearning Papers, Language Learning and Technology issue reviewer; ICWL 2015 program board member; International Conference on Learning and Collaboration Technologies, HCII, program board member

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DISSERTATIONS ON NATURAL SCIENCES

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