Action Research and Learning Analytics in Higher Education

Von der Fakultät für Mathematik, Informatik und Naturwissenschaften der RWTH Aachen University zur Erlangung des akademischen Grades einer Doktorin der Naturwissenschaften genehmigte Dissertation

vorgelegt von

Diplom-Informatikerin

Anna Lea Dyckhoff

aus Hagen

Berichter:

Universitätsprofessor Dr.-Ing. Ulrik Schroeder

Professor Dr. Marcus Specht

Tag der mündlichen Prüfung: 6. Juni 2014

ABSTRACT

Teaching can be very effective, if its impact is monitored and adjusted to the demands of changing social contexts and needs of learners. This implies that teachers need to be aware and reflect about teaching and learning processes.

In the last years, a rising interest in 'learning analytics' is observable. This interest is motivated by the availability of massive amounts of educational data. Also, the continuously increasing processing power, and a strong motivation for discovering new information from these pools of educational data, is pushing further developments within the learning analytics research field. Learning analytics could be a method for reflective teaching practice that enables and guides teachers to investigate and evaluate their work in future learning scenarios. However, this potentially positive impact has not yet been sufficiently verified by learning analytics research.

Another method that pursues these goals is 'action research'. Learning analytics promises to initiate action research processes because it facilitates awareness, reflection and regulation of teaching activities analogous to action research.

Therefore, this thesis joins both concepts, in order to improve the design of learning analytics tools. Central research question of this thesis are: What are the dimensions of learning analytics in relation to action research, which need to be considered when designing a learning analytics tool? How does a learning analytics dashboard impact the teachers of technology-enhanced university lectures regarding 'awareness', 'reflection' and 'action'? Does it initiate action research? Which are central requirements for a learning analytics tool, which pursues such effects?

This project followed design-based research principles, in order to answer these research questions. The main contributions are: a theoretical reference model that connects action research and learning analytics, the conceptualization and implementation of a learning analytics tool, a requirements catalogue for useful and usable learning analytics design based on evaluations, a tested procedure for impact analysis, and guidelines for the introduction of learning analytics into higher education.

ZUSAMMENFASSUNG

Lehre kann sehr effektiv sein, wenn ihr Einfluss gemessen sowie an die sich verändernden Anforderungen und sozialen Kontexte der Lerner angepasst wird. Dies bedeutet indirekt, dass Lehrende sich über Lehr- und Lernprozesse bewusst sein müssen und darüber reflektieren sollten.

In den letzten Jahren ist zu beobachten, dass das Interesse an ‚Learning Analytics' zunimmt. Motiviert wird dies häufig durch die Verfügbarkeit der großen Datenmengen aus dem Bildungsbereich. Zudem wird dieser Forschungsbereich durch kontinuierlich besser werdende Verarbeitungsmöglichkeiten und die starke Motivation, neue Informationen aus den Datenmengen abzuleiten, vorangetrieben. Learning Analytics könnte eine Methode für reflektierendes Lehren sein, welche es Lehrenden ermöglicht, ihre Arbeit zu untersuchen und zu evaluieren. Jedoch wurde dieser potentiell positive Einfluss bisher noch nicht ausreichend durch Learning-Analytics-Forschung nachgewiesen.

Eine weitere Methodik, die sich diese Ziele setzt, ist die ‚Aktionsforschung'. Learning Analytics verspricht, Aktionsforschung zu initiieren, weil es Bewusstsein, Reflektion und die Regulation von Lehraktivitäten analog zu Aktionsforschung fördert.

Vor diesem Hintergrund, vereint diese Doktorarbeit beide Konzepte, um die Gestaltung von Learning-Analytics-Werkzeugen zu verbessern. Zentrale Fragestellungen dieser Dissertation sind: Welche Learning-Analytics-Dimensionen gibt es in Bezug auf Aktionsforschung, die bei der Gestaltung eines Learning-Analytics-Werkzeugs in Betracht gezogen werden sollten? Welchen Einfluss hat ein Learning-Analytics-Dashboard auf Lehrende technologie-gestützter Universitätslehrveranstaltungen in Bezug auf ‚Bewusstsein', ‚Reflektion' und ‚Aktion'? Initiiert es Aktionsforschung? Welche sind die wichtigsten Anforderungen an ein Learning-Analytics-Werkzeug, welches solch eine Wirkung haben soll?

Diese Doktorarbeit folgte ‚Design-based Research'-Prinzipien, um diese Forschungsfragen zu beantworten. Die wesentlichen Forschungsbeiträge sind: ein theoretisches Aktionsforschung mit Learning Analytics verknüpfendes Referenzmodell, die Konzeption und Implementierung eines Learning-Analytics-Werkzeugs, ein Anforderungskatalog bezüglich nützlicher und benutzbarer Learning-Analytics-Designs basierend auf Evaluationen, eine getestete Vorgehensweise zur Evaluation des Einflusses von Learning Analytics sowie Richtlinien für die Einführung von Learning Analytics in die Hochschullehre.

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1 INTRODUCTION

The field of ‘learning analytics’ has been accredited with high relevance for prospective developments in technology-enhanced learning (TEL) in higher education in the latest Horizon Reports (L. Johnson et al. 2011; L. Johnson, Adams, and Cummins 2012; L. Johnson et al. 2013). Additionally, current publicity of ‘massive open online courses’ (MOOCs) directs further attention to learning analytics with the promise to tell its users more about learning processes (e.g., Mackay 2013).

One of the most frequently named reasons for the rising interest in analytics can be found in the availability of massive amounts of educational data, the continuously increasing processing power, and the motivation for discovering new information from these data pools. As blended learning scenarios at universities, where ‘virtual learning environments’ (VLE) are integrated into the learning process, are becoming standard, data from several sources, such as data from educational software but also from face-to-face classroom environments can be collected (Cristóbal Romero et al. 2011). Analyzing this data can make pieces of information visible that previously has been “*unseen, unnoticed, and therefore unactionable*” (Cator and Adams 2012). Predictions of research tell us that such analytics would potentially have high impact by placing “*more and better information into the hands of a greater number of people, enabling informed decision-making*” (J. P. Campbell, DeBlois, and Oblinger 2007). But a closer look shows: Learning analytics finds its way into daily practice at universities rather hesitant because of data privacy concerns, conflicting interests of different groups of stakeholders, and missing concepts for its applicable integration. This thesis carefully investigates these issues from teaching perspective and intends to provide guidance for future developments in learning analytics, and their adequate integration into higher educational practice.

Teaching is a dynamic activity that can be considered effective, if its impact is constantly monitored and adjusted to the demands of changing social contexts and the needs of the learners. This implies that teachers need to be aware about teaching and learning processes. Moreover, they should constantly analyze, reflect, regulate, and update their didactical methods and the learning resources they provide to their students.

A teacher can observe his or her students during the process of learning. Of course, only a fraction of the students' behavior is actually visible. Additionally, we usually try to measure the learning outcomes as proof for learning. The ideal teacher should observe and adjust his or her teaching to each individual student, just like a mother or father carefully fits her or his speech and behavior to the abilities of a child. Unfortunately, most teachers have often a lot of students. Furthermore, these students are not always nearby and easy to observe, especially in TEL. However, based on the observed activities of their students, teachers can reflect on the status of learning of their students. They should also self-reflect upon their own actions, their didactical methods, and available materials.

'Self-reflection' has been defined as a conscious activity, exploring ones experiences, in order to gain new insight and appreciation (Boud, Keogh, and Walker 1985). The process of self-reflection can be described as a cyclical learning activity, where 'concrete experience' leads to 'reflective observation' which in turn supports 'abstract conceptualization' (Kolb 1984). Loops of active reflection and improvement activities for creating better learning environments can also be found in 'educational action research'. Action research is a method for reflective teaching practice that enables and guides teachers to investigate and evaluate their work (Altrichter, Posch, and Somekh 2005). Hinchey defines action research as "*a process of systematic inquiry, usually cyclical, conducted by those inside a community rather than outside experts; its goal is to identify action that will generate improvement the researchers believe important*" (Hinchey 2008). Therefore, the goal of action research is not the generalizability of findings, but rather practical relevance.

Educators should keep on asking questions about the effectiveness of TEL and evaluate how their teaching can further be improved. Successful educators are those who can make effective use of the available data and, thereupon, make better decisions, and develop better teaching strategies.

Hence, the fundamental assumptions of this thesis are twofold:

- Learning anlytics initiate and support action research.
- Action research, which is carried out by the teachers and learners themselves, leads to quality improvement in TEL.

Learning analytics could take a role similar to an external researcher or action research mentor, who identifies a problem and brings it to the attention of a group of stakeholders, as described by Berg (2001a). Expected improvements are then founded in the iterative evaluation activities of action research projects, including data collection, analysis, (self-)reflection, and consequent redesign of learning designs.

This thesis investigated, how learning analytics tools can initiate and support action research activities. For this purpose, an 'exploratory Learning Analytics

Tool' (eLAT) has been iteratively designed, developed, and tested with the objective to expand teachers' perceptions and reflection possibilities regarding TEL scenarios. The concept and implementation stages of eLAT as well as its impact on teachers' behaviors have been evaluated involving TEL courses at RWTH Aachen University. Through this commitment to real world learning scenarios, it was possible to have a full overview of the situation, draw realistic conclusions, and create suitable guidelines for development of future learning analytics tools.

This chapter proceeds as follows: Section 1.1 continues with further motivation about the research subject. Section 1.2 further defines the research questions. Section 1.3 summarizes major contributions and, finally, section 1.4 outlines the overall structure of this thesis.

1.1 Motivation

Many universities provide centrally maintained VLEs and invite their teaching staff to blend online and face-to-face teaching methods, in order to meet expectations of young scholars. For instance, RWTH Aachen University's Center for innovative Learning Technologies (CiL) aims at the sustainable development of blended learning cultures facilitated through the provision of the learning and teaching portal L^2P, which offers standard functionalities of learning managements systems.[1] Looking at the number of courses, which are supported by L^2P, blended learning has been widely adopted at RWTH (Schroeder 2009).

However, it can be observed that teachers are not able to fully exploit the potential of such a system with regard to new ways of collaborative teaching and learning. In all learning scenarios – from traditional learning scenarios over TEL to distance education – teachers have to be aware of how students engage in the learning process. They need to know whether and where their students experience difficulties, where they should adjust the teaching activities and resources to address all students' needs, and how they can guide them to become successful learners. Therefore, monitoring and reflecting the students' learning processes are essential for high quality education. This is even more crucial in distance education, where there are other types of social interactions and often fewer possibilities for contact with teachers and other students (Mazza and Dimitrova 2004). However, when the research for this thesis was started, most VLEs did not provide or provided rather simplistic analytics features for monitoring the students' data (Cristóbal Romero, Ventura, and García 2008). Therefore, this channel of reflection was limited. As chapter 2 demonstrates by giving an overview on related work, several learning analytics tools have emerged since then. Out of these projects, only few pay close attention to the ways learning

[1] The abbreviation L^2P stands for ‚Lehr- und Lernportal' (www.elearning.rwth-aachen.de).
[2] The selection is based on Hinchey (2008).

analytics foster reflection and so far action research methodology has not been taken into account.

Reflection can foster learning, if it is embedded in a cyclical process of active experimentation (Kolb 1984). A teacher, who is involved in such processes of action, observation and reflection, can be described as a practitioner of action research. Action research is a method for reflective teaching practice that enables and guides teachers to investigate and evaluate their work (Altrichter, Posch, and Somekh 2005). A positive outcome of action research should be an increased awareness concerning the unique aspects of a learning scenario, pushed improvements as well as the development of personal teaching skills.

Learners differ among many factors. Diverse variables, such as differences in motivation, cognition, learning styles or strategies, preferences, awareness and self-reflection, might influence the learning process of students. But also cultural diversity, age, or gender may have an effect. There is no teaching method that is equally well suited for all students (Schulmeister 2004a). Schulmeister discusses that awareness of diversity issues, adaption of teaching methods, and open learning environments can help specific groups of students to become more successful learners. Hence, the effectiveness of a teaching method depends on the target group, its context, and the ability of the teacher to adjust to it, and accordingly create open learning scenarios. A conclusion is that teachers should have comprehensive insight into the requirements and learning behaviors of specific groups of students, in order to get to know them, derive conclusions about them, and create suitable action plans for adapting their teaching accordingly.

The research field of learning analytics explores methods and tools for visual analysis and pattern recognition in educational data to permit institutions, teachers, and students to iteratively reflect apon observable learning behaviors and processes and, thus, call for the optimization of learning designs and aid the improvement of learning (Lockyer and Dawson 2011; Chatti et al. 2012a; Chatti et al. 2012b).

This thesis is based on the assumption that learning analytics tools can initiate and support action research, especially if they are designed to meet action research requirements. In action research projects, a learning analytics tool could take the role of an action research mentor, who provides helpful tools and information, but leaves important analysis and action decisions to the user. To ensure broad acceptance, even teachers without in-depth education of information technology and media education must be able to use these tool, independently perform analyses, and interpret the learning analytics results correctly (Zielke 2011).

Current learning analytics tools usually provide several kinds of metrics. The amount of information could easily be overwhelming for users. To alleviate this situation, these tools should provide collections of research questions and guide the users in selecting own questions, perform data collection, and facilitate active analysis based on a particular users' interests and course contexts. This could be achieved by acknowledging action research characteristics within the requirements analysis and design of LA tools. Therefore, learning analytics should be informed by action research characteristics (A. L. Dyckhoff 2011; A. L. Dyckhoff, Lukarov, Muslim, et al. 2013).

1.2 Objectives

The overall purpose of this thesis is the improvement of TEL in higher education. Especially educators, who are just beginning to create blended learning scenarios, e.g., by using VLEs for the first times, want to learn how this affects the behaviors of different groups of students. They should be initiated to iteratively enhance and improve their courses based on practical experiences. Therefore, these teachers need support for monitoring and analyzing their students' learning progress as well as acting upon their findings. A combination of action research with learning analytics promises to initiate this process.

Hence, the central research questions are:

- What are the dimensions of learning analytics in relation to action research, which need to be considered when designing a learning analytics tool?
- Which are the areas of conflict? And how could they be dealt with?
- How can an integrated learning analytics dashboard influence typical German university lectures (beginners and advanced users), which make use of a VLE?
- Which learning analytics indicators are most meaningful to whom?
- How does a learning analytics dashboard impact the teachers of TEL university lectures regarding 'awareness', 'reflection' and 'action'? Does it initiate and support 'action research'?
- What are the advantages and drawbacks (effects) of introducing a learning analytics tool into technology-enhanced university courses? What needs to be considered?
- Which variables influence the impact of learning analytics usage? How is the impact influenced by personal and contextual factors?
- Which are the central requirements, which make a learning analytics tool useful for influencing teachers' awareness of students' online learning behaviors and diversity, reflection on the quality of their teaching, and action regarding findings from data exploration in order to improve their teaching?
- How should we design respective action research and learning analytics user interfaces?

The field of learning analytics promises to facilitate awareness, reflection and regulation of teaching activities analogous to action research. Therefore, it is a logical conclusion to connect learning analytics with action research as a theoretical basis for the developed tools in the thesis at hand.

1.3 Contributions

In order to answer the research questions, this thesis followed design-based research principles (Reeves, Herrington, and Oliver 2005; Baumgartner et al. 2003) as well as the seven design science guidelines described by (Hevner et al. 2004), resulting in the following contributions (Figure 1):

- *ARLA reference model*: The abbreviation ARLA stands for action research (AR) and learning analytics (LA). The ARLA reference model is based on prior LA reference models. Based on findings of this thesis, the model refines these and completes them by connecting AR with LA.
- *eLAT*: The 'exploratory Learning Analytics Tool' (eLAT) was conceptualized, designed, and implemented by following standard design-based educational research methods. Its design process facilitated the collection and verification of requirements in higher education.
- *Impact evaluation*: A qualitative evaluation method was designed based on suitable user experience methods and tested within university lectures. The findings of the impact evaluation informed the development towards a final ARLA model.
- *ARLA model and architecture*: The findings have been described and specified by implementing and evaluating user interface prototypes of ARLA tools. The model includes an ARLA catalogue of requirements and guidelines. This catalogue helps to establish good LA designs based on AR methodology. Furthermore, it provides guidelines for application of LA in higher education, while considering data privacy issues.

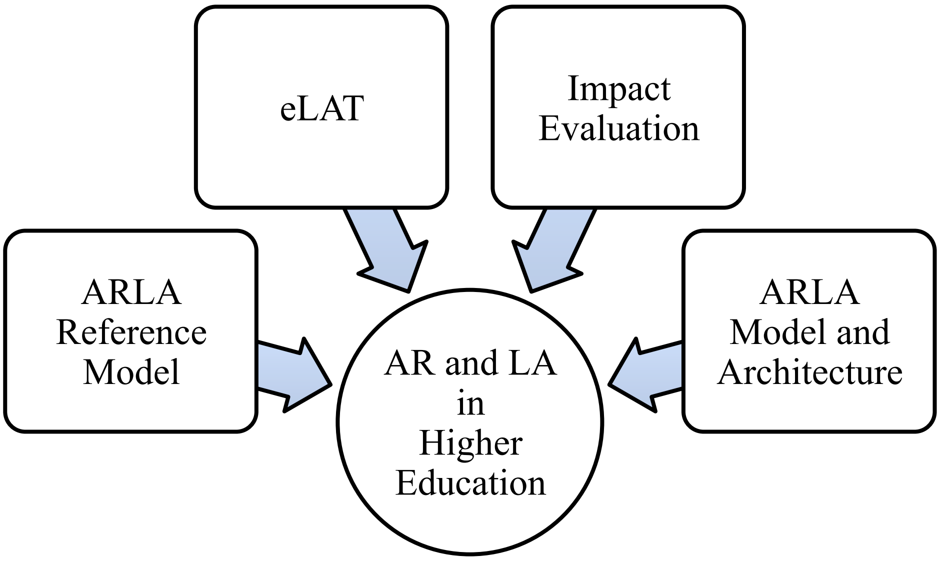

Figure 1. Contributions.

1.4 Outline

The thesis at hand is organized into nine chapters. The following paragraphs provide brief descriptions of each chapter.

Chapter 2 gives an overview on related work regarding AR and LA and their combination.

Chapter 3 presents the overall concept of the basic method, which was applied, in order to reach the objectives and answer the questions defined in chapter 1. Therefore, it briefly introduces the general concept of design science and design-based research guidelines.

Chapter 4 gives an introduction into the fundamental terms and concepts of this thesis regarding the research goals. In order to study how LA influences its users, we need to understand awareness, reflection, and action. Furthermore, this chapter helps to distinguish the field of LA from other related fields, such as academic analytics or educational data mining, by defining its scope.

Chapter 5 describes the reference model for AR and LA, which supports the classification of LA projects, while making AR more visible. The ARLA reference model represents the connection of both fields. It is the basis for an illustration of the ARLA processes, which demonstrate how the introduction of LA can lead to reflection and action. This model serves as a basis for discussions and conclusions in the subsequent chapters.

Chapter 6 presents the iterative design process of developing and evaluating the teacher-centered tool ‘eLAT’, which led to the development of the models and concepts described in this work. The chapter highlights the main prototyping stages of eLAT, which focused on different aspects, like the overall system architecture and different user interfaces. The practical experiences of implementing and evaluating these prototypes supported the compilation of guidelines and a specification based on a catalogue of qualitative requirements for an ARLA tool.

Chapter 7 reviews the experience of a pilot phase with real courses in more detail. This study evaluated the effects of eLAT on teaching. It specifically focused on the impact of using this LA tool regarding awareness, reflection and action. The chapter also delineates several use cases, which had been observed during the evaluation and discusses possible future trends as well as major implications for future LA tools. The observed processes and findings of this evaluation supported the refinement of the ARLA reference model and the ARLA process model as well as the collection of requirements for respective implementations.

Chapter 8 is dedicated to the ARLA model and architecture contributed by this work. Furthermore, it summarizes recommended procedures (guidelines) regarding layout and the application of LA in higher education.

Finally, chapter 9 discusses different aspects of the work done in this research. It summarizes the main contributions and outlines possible extensions as well as future challenges.

2 RELATED WORK

„*[A]ll the important stuff with analytics happens...after we've done the analytics*" state Siemens's slides of a focus session regarding the topic 'Sensemaking: Beyond Analytics As A Technical Activity' (Siemens 2012a). It is the goal of this work that this 'important stuff' is reflection on newly gained knowledge, action and behavior change. The Wikipedia article on 'Learning Analytics' (LA) actually mentions the term 'intervention' in its methods section. However, so far it has not been filled with meaning(s), at least in the open encyclopedia (Wikipedia 2013a).

Several action researchers have created AR frameworks. These are guidelines that are supposed to help practitioners to perform this methodology with more ease. Nunes and McPherson (2004), e.g., argue that AR is particularly appropriate for online learning. They describe an educational model as a guide for everyday work and professional life, which is called Educational Management Action Research (EMAR). It is an ongoing and iterative approach because of the persistent need for improvement in e-learning. A driving factor for its creation was the question: What is the best way to manage change in education? So, Nunes's and McPherson's answer is 'action research' because it is an "*approach for knowledge creation, reflection and application in action*". Although it is powerful, a criticism of EMAR is that it still might be too complex for single teachers to implement, at least without the help of professional action researchers. Furthermore, LA is not integrated within it.

Siemens and Long (2011) view LA itself as a model for systemic change: "*[A]nalytics provides a new model [...] to improve teaching, learning, organizational efficiency, and decision making and, as a consequence, serve as a foundation for systemic change*" (Siemens and Long 2011). But how does this model look like? An answer to this question is the LA Reference Model (Chatti et al. 2012a). It presents the dimensions of LA and elaborates them in more detail. Additionally, several LA researchers have presented their thoughts on LA processes (Chatti et al. 2012a; Clow 2012; Elias 2011; Verbert et al. 2013). These models will be presented and compared in chapter 4 and 5. They are mainly concepts, which have not been evaluated yet.

Literature reviews and analysis within this thesis' work have not found research that combines AR with LA, although there are many similarities between both concepts (A. L. Dyckhoff, Lukarov, Muslim, et al. 2013). After the third

International Learning Analytics & Knowledge Conference in 2013 (LAK 2013) this lack of research has been acknowledged by a call for papers for a special issue of the British Journal of Educational Technology. This journal issue seeks to explore the synergy between teacher-led inquiry into student learning, learning design, and LA:

> "*For learning design to be effective, it should be informed and evaluated by teacher inquiry or should form part of a process of inquiry. For TISL to be meaningful, it should support the design of activities and resources. Together, these suggest an integrated dynamic model of teaching as design inquiry of learning. The recent emergence of learning analytics as a field offers to equip learners and teachers with powerful new tools that can support their inquiry into learning practices.*" (Zeiliger 2013)

In the last decade, several studies on tools that more or less can be classified as LA tools have been published (Arnold 2010; Bakharia, Heathcote, and Dawson 2009; Bratitsis and Dimitracopoulou 2005; Bratitsis and Dimitracopoulou 2006; Bratitsis and Dimitracopoulou 2008a; Bratitsis and Dimitracopoulou 2008b; Brooks, Panesar, and Greer 2006; Ali et al. 2012; Merceron and Yacef 2005; Krüger, Merceron, and Wolf 2010; Scheuer and Zinn 2007; Zorrilla, Marín, and Álvarez 2007; Zorrilla, García, and Álvarez 2010; Mazza 2006; Mazza and Dimitrova 2007; Tally 2009; Fritz 2011; Zhang et al. 2007; May, George, and Prévôt 2011a; May, George, and Prévôt 2011b; Pedraza Perez, Romero, and Ventura 2011; M. W. Johnson et al. 2011; Graf et al. 2011; Kosba, Dimitrova, and Boyle 2005; García-Saiz and Pantaleón 2011; De Groot et al. 2007; González Agulla et al. 2009; Schmitz, Scheffel, et al. 2009; Govaerts et al. 2012; Petropoulou et al. 2007; Dawson 2010; Mochizuki et al. 2007; Janssen et al. 2007; Beuster et al. 2013).

The following paragraphs give brief summaries of a selection of these related works; e.g., LA tools can have different target groups, such as teachers, students, researchers, moderators, and instructional designers. Since the goal of this dissertation work is to support teachers in improving their pedagogical practice based on student data monitoring, analysis, and reflection, the related works discussion is mostly focused on projects with similar goals.

It is notable that the research projects try to achieve common purposes. Many of them aim at increasing awareness and reflection about the learning process; fostering improvement activities at best. LA is supposed to help teachers to reflect and draw conclusions on the quality of their learning content, pedagogical practice, and quality of interactions among students (e.g., Ali et al., 2012; Graf et al., 2011; Merceron & Yacef, 2005; Scheuer & Zinn, 2007; Marta Elena Zorrilla & Álvarez, 2008), while students are to be stimulated to self-reflect on their learning behavior based on monitoring their own usage/interaction behavior as well as having comparative information at hand (see, Fritz, 2011; Janssen et al., 2007; Mochizuki et al., 2007; Schmitz, Scheffel, et al., 2009).

Ali et al. (2012) iteratively developed an LA tool, called LOCO-Analyst to „*provide educators with feedback on students learning activities and performance*“ (Ali et al., 2012, p. 470). The tool „*aims at helping them rethink the quality of the employed learning content and learning design*“ (Asadi et al., 2011, p. 14). LOCO-Analyst „*provides educators with feedback regarding student activities, usage and comprehensibility of the learning content, and contextualized social interactions among students*” (Asadi et al. 2011). The researchers used quantitative and qualitative evaluation methods to evaluate the perceived usability and usefulness of prototype stages of LOCO-Analyst, especially focusing the evaluation on effects of enhancing the user interface with data visualizations (Ali et al. 2012). The main result was that visualizing data in multiple ways, rather than representing it in a tabular format, increased the perceived value of the LA tool (Ali et al. 2012, p. 488).

Merceron & Yacef (2005) introduced TADA-Ed, a Data Mining Tool for Advanced Data Analysis in Education. It provides support in filtering and preprocessing available data and „*integrate[s] various visualization and data mining facilities to help teachers in discovering pedagogically relevant information*“ (Merceron & Yacef 2005, p. 1). The „*aim is to have a tool that can exploit students' interactions, web logs as well as data with richer semantic information such as the relevance of an action, the evaluation of correctness and, if applicable, the type of mistake made*“ (Merceron & Yacef 2005, p. 1). TADA-Ed includes classification, clustering, and association rule algorithms. It has been used to detect clusters of mistakes students made, which led to reflection on course materials. However, probably only teachers who have data mining knowledge can use the version of TADA-Ed presented in 2005 because data mining vocabulary is used thoughout the user interface and parameters of algorithms have to be chosen to receive further results.

Beuster et al. (2013) present LeMo, an LA tool for monitoring the learning process. Their objective is to support teachers, researchers and providers of e-learning in the analysis of usage data of their online learning and blended learning scenarios. LeMo can include data of several VLEs and online platforms. It provides various indicators, e.g., regarding the analysis of activities over time spans, average usage of learning offerings, identifying frequent learning paths, and overviewing average test results. The development was focused on ease of use and dynamic visualizations of analytics results.

Scheuer & Zinn (2007) devised an LA tool for teachers, called ‘Student Inspector’. In summer 2006, they conducted a study to better understand teachers’ requirements for the desired tool. The findings of the study “*revealed a clear preference for pedagogically-oriented measures, namely, overall success rate, a learner’s mastery levels and typical misconceptions, the percentages of exercises tackled, and amount of material read*” (Scheuer & Zinn, 2007, p. 488). Other information, like navigational style and social data, attracted less interest; teachers judged them as too cumbersome to inspect or too time-intensive to interpret.

Student Inspector allows exploring student data and additionally gives access to predictive artificial-intelligence-based analyses for expert users. Users may change parameters and therefore explore the data based on their interests. The system supports analyzing data of individual students as well as data of groups of students. Student Inspector has been evaluated by a survey. Given a series of screenshots, participants were asked to evaluate the tool regarding usefulness, ease of use, functionality, organization of information, and terminology (Scheuer & Zinn, 2007, p. 492). The main results of the evaluation showed that visualizations of information were a benefit for ease of use. Teachers also welcomed to examine student performance trends and liked to be informed about giving feedback to students. However, some participants feared that using all the features of the interface could be too time-consuming and overwhelming for some users.

Zorrilla et al. (2007) described a Monitoring and Analysis Tool for E-learning Platforms (MATEP), which was developed to help teachers to understand how their students use web-based learning environments. An important aim regarding MATEP was to deliver answers to questions regarding students' learning behavior and provide better decision support for teachers based on VLE log data analysis. According to Zorrilla et al. (2007), teachers need specific reporting tools to *"[...] monitor, understand and assess the distance learning process of students [...]"* (Zorrilla et al. 2007, p. 392). "*This would allow them to re-structure the course according to its use, design the course activities according to the resources they have used, propose activities which encourage students to follow the course regularly and so on.*" (Zorrilla et al., 2007, p. 393). A first prototype of MATEP provided analysis results in form of tables and simple data visualizations, like bar charts (Zorrilla et al., 2007). Later versions of the tool included data mining analysis options, such as clustering students or session information according to usage behavior, and visualized results in form of radar graphs and tables (Zorrilla et al. 2010). In order to evaluate enhancements made within MATEP, the visualized reports were shown to one teacher. Her feedback revealed that the reports allowed her "*[...] to gain an insight into the characteristics of her students with relation to the time spent and the use of resources available in the course*" (Zorrilla et al. 2010, p. 7). However, she also criticized the complex presentation of the results (radar graphs) and suggested using additional textual explanations (Zorrilla et al. 2010, p. 7). The researchers did not evaluate, if MATEP actually provokes teachers to modify their teaching style, e.g., reorganize content, propose new tasks, open a discussion, etc.

Mazza & Dimitrova (2007) studied graphical user interfaces for Educational Data Mining (EDM) tools. The design of 'CourseVis' was based on the results of a survey, which revealed that instructors need information on social, cognitive, and behavioral aspects about their students when running distant education courses with a VLE. CourseVis used web log data and rendered it graphically in form of, e.g., a 3D scatter plot or a 3D matrix. The main goal of the tool was to increase awareness about the learning process and provide different perspectives on monitoring data by rotation and zoom features. Evaluations by focus groups and experimental studies with semi-structured interviews have shown that the graphical representations of CourseVis helped instructors to quickly and more accurately grasp information of students (Mazza 2006). However, previous knowledge and experience with interpretation of the 3D-visualizations seems to be necessary to understand the information timely. As a follow-up, the successful visualization principles of CourseVis have been implemented with a graphical interactive plug-in for student monitoring in Moodle, called GISMO (Mazza and Botturi 2007).

Zhang et al. (2007) introduced a log analysis plugin for the LMS Moodle, which they called 'Moodle Watchdog' (Moodog). Moodog aims at providing teachers with data about how students interact with online course materials. They can act upon this information by sending emails to students. Additionally, the system automatically sends reminders to students, who have not accessed a specific course material. Furthermore, Moodog allows students to compare their own progress to others in a course (Zhang et al. 2007). It provides statistical reports and visualizations related to the four categories: course summary, per-student statistics, per-resource statistics, and time-based statistics. Notably, the tool also supplies information about resources that have not been accessed and students, who have not accessed specific resources, respectively. Some visualizations are located directly beside resources within the Moodle interface. Other visualizations are included within data tables. As a case study, the researchers conducted an off-line analysis with data of a finished course. One of the findings, e.g., showed a positive correlation between a student's forum activity and the overall course grade. However, since only data from one course was analyzed, this finding could be ascribed to other course related factors. Zhang et al. (2007) mentioned a plan to evaluate the impact of Moodog on educators' and students' behavior.

Schmitz et al. (2009) developed a tool for monitoring and reporting on learning behavior, called CAMera. In contrast to the other tools described, students are the main target group of CAMera, which is supposed to support them in self-reflecting their learning activities. The tool can collect data from a set of application programs running locally on a student's computer and store it locally and remotely on a server in the Contextualized Attention Metadata (CAM) format. "*Contextualized attention metadata describe which data objects attract the users' attention, which actions users perform with these objects and what the use contexts are*" (Schmitz, Wolpers, Kirschenmann, & Niemann, 2009, p. 1). Therefore, "*[t]he CAM schema is designed to allow tracking user activities in all systems [the user] may interact with while working with documents*" (Wolpers et al., 2007, p. 110). CAMera includes two analyzing components: the email analyzer and the Zeitgeist application: The email analyzer exclusively analyzes a student's email usage, while the Zeitgeist application monitors and analyzes the interactions of several students within a personal learning environment, called MACE. The email analyzer is supposed to support each user in reflecting his and her communication behavior. It provides visualizations of a social network, which is derived from email exchange data. By clicking on nodes, keywords, or specifying a time interval, the user can browse and explore the network data to get more information on particular persons or keywords of messages. The Zeitgeist application is web-based and provides an overview of activities within the MACE system, e.g., users may reconstruct their learning paths or topics of interest. CAMera has not been formally evaluated, yet, to prove that usage of the tool leads to self-reflection and better learning outcomes. But evaluations within the European research project ROLE (Responsive Open Learning Environments) are planned (Schmitz, Scheffel, et al. 2009).

Govaerts el al. (2012) iteratively developed the Student Activity Meter (SAM), which visualizes learning activities for both, teachers and students, to support self-reflection. They applied a design-based research methodology to evaluate the usefulness and usability of different visualization techniques. SAM provides analysis of the time students spent on learning activities and documents usage statistics. As CAMera, SAM relies on CAM (Schmitz, Wolpers, et al. 2009). Users can interact with the data analysis results by zooming in or clicking on components of visualizations, which are presented within a dashboard overview. Evaluations with students showed that most users were able to use SAM, but first-time users might need some help because of complex visualizations (e.g., clustered line charts and parallel coordinates. Furthermore, the students liked to see how much others worked on the course for comparison (Govaerts et al. 2012). Evaluations with teachers showed that it is important for them to provide feedback to students, followed by student awareness and resource use. A limitation of the studies was that users were only exposed to SAM for a brief periods of time before the evaluation. The impact on the behavior of students and teachers of integrating such a tool in a learning environment should be investigated by further studies.

Bratitsis & Dimitracopoulou (2005) introduced a Discussion Interaction Analysis System (DIAS), which supports teachers in analyzing students' interactions in a discussion forum and which helps them to identify situations that require intervention (Bratitsis and Dimitracopoulou 2008a). The system computes data indicators, which serve for the evaluation of the discussion activity and social dimensions of students. DIAS can produce a wide range of visualized indicators, varying from simple statistical information to more complex cognitive and metacognitive indicators and addressing different target groups, such as researchers, moderators (e.g., teachers) or students (Bratitsis and Dimitracopoulou 2008a). The indicators can be divided into four categories: individual point of view, differentiated as well as undifferentiated group point of view, and community point of view (Bratitsis and Dimitracopoulou 2008b). During case studies the researchers assessed the indicators' correctness, its usage as well as their effect on students (and teachers) behavior. According to Bratitsis & Dimitracopoulou (2008), "*indicators affect the users, operating as a very powerful motive for increasing activity*" (p. 537). Users especially liked to access comparative information (differentiated group point of view). Furthermore, participants, who knew how to interpret SNA diagrams, seemed to be tighter connected with more collaborators. The researchers concluded that the DIAS indicators "*affect users and the learning process at extension*" (p. 538). The students' effort to improve their interaction status led to more critical thinking and sustained effective discussions. Findings also revealed that some students made attempts to improve their discussion analysis data related to other students without contributing to the discussion with regard to content. E.g., in one case a student tricked the system by writing several messages in a short time span in order to appear as one of the most active users (Bratitsis and Dimitracopoulou 2006). By combining information of several indicators, teachers could detect such unexpected behavior. Concerning transparency of the indicators, participating teachers suggested to additionally provide interpretation instructions, including examples and schemas of utilizing the information to the teachers' benefit (Bratitsis and Dimitracopoulou 2008b).

Many LA tools have been implemented with respect to goals similar to the objectives of AR because they aim at supporting awareness and reflection, or even action. But this connection is not explicit.

Table 1 presents several goals of LA. These overall goals have been detailed and formulated in several ways. They can be divided into goals that

a. explicitly inform the design of LA tools.
b. involve a behavioral reaction of the teacher.
c. involve a behavioral reaction of the student.

Strikingly, there are very few publications reporting about findings related to the behavioral reactions of (b.) teachers and (c.) students, i.e., few studies measure the impact of using LA tools. But besides the perceived value of LA this is important. How do these systems influence practical learning situations?

Evaluative research on state-of-the-art tools focuses on functionality, usability issues (indicator design, comprehensibility, terminology) and perceived usefulness of specific indicators (Ali et al., 2012; Govaerts et al., 2012; Mazza, 2006; Scheuer & Zinn, 2007). Furthermore, possibly due to novelty reasons several projects have not yet published data about conducting reliable case studies or evaluations results at all (e.g., García-Saiz & Pantaleón, 2011; Graf et al., 2011; Pedraza Perez et al., 2011; Schmitz, Scheffel, et al., 2009). Some have conducted rather small evaluations that limit generalization of conclusions; e.g., M. Zorrilla et al. (2010) tested MATEP with one teacher. Although May et al. (2011b) mentioned that their experimental study aimed at measuring impact on the learning situation, they could not make conclusions because of a low participation rate. Bratitsis & Dimitracopoulou (2008b) give some evidence for the effects of using LA on teachers' and students' behaviors. They concluded that discussion analysis indicators helped to increase students' activity, which might affect the learning process by leading to more effective discussions and critical thinking.

Table 1. Objectives of LA. Adapted from Dyckhoff et al. (2013)

<table>
<tr><th colspan="2">a. LA tools are supposed to</th></tr>
<tr><td colspan="2">• gather data / track user activities
• capture the interaction of students with resources / the interactions among students
• provide educators / students with feedback/information on students' activities
• provide an overview
• highlight important aspects of data
• provide different perspectives
• offer possibilities for (peer) comparison
• draw the users attention to interesting correlations
• pinpoint problematic issues
• establish an early warning system
• provide decision support</td></tr>
<tr><th>b. educators are supposed to</th><th>c. students are supposed to</th></tr>
<tr><td>• monitor learning process / way of learning / students' effort
• explore student data
• get to know students' strategies
• identify difficulties
• discover patterns
• find early indicators for success / poor marks / drop-out
• draw conclusions about usefulness of certain learning materials
• draw conclusions about students' success factors
• become aware
• reflect / self-reflect
• better understand effectiveness of learning environments
• intervene / supervise / advice / offer assistance
• improve quality of teaching / learning materials / environment</td><td>• monitor own activities / interactions / learning process
• compare own behavior with the whole group / high performing students
• become aware
• reflect / self-reflect
• improve discussion participation / learning behavior / performance</td></tr>
</table>

Nevertheless, all these tools did not evaluate their goals sufficiently. Therefore, this work combined AR theory with LA to create an improved reference model. Additionally, it developed own tools based on this model, and conducted an impact evaluation.

3 METHOD

The main goal of design science is to gain knowledge and understanding by creating new and innovative artifacts and models. Hevner et al. (2004) present a conceptual framework and guidelines for conducting design-based research on information systems. The methodology of this thesis is based on these guidelines, which are therefore briefly presented and explained.

3.1 Design-Science

Hevner et al. (2004) compare design science to behavioral-science research as "*two sides of the same coin*" (p. 77). The latter seeks to predict "*phenomena that occur with respect to the artifact's use (intention to use), perceived usefulness, and impact on individuals and organizations (net benefits) depending on system, service, and information quality*" (p. 77) – or in short: it seeks for "*truth*". On the other side, the purpose of design science is "*utility*", which is obtained through the design and evaluation of innovative artifacts. According to the researchers, design is "*the purposeful organization of resources to accomplish a goal*" (p. 78). It is also "*both a process (set of activities) and a product (artifact)*" (Walls, Widmeyer, and El Sawy (1992) as cited by Hevner et al. 2004, p. 78). Similar to AR, the design research process is an iteratively conducted "*build-and-evaluate*" loop. It is different from AR because it results in the design artifact, while AR leads to improved situations. It is different from routine design, because it is not building on existing knowledge to problems, but "*addresses important unsolved problems in unique or innovative ways or solved problems in more effective or efficient ways*" (Hevner et al. (2004), p. 81).

Hevner et al. (2004) define essential characteristics of design science problems, which apply to the research problem described in chapter 1, namely:

- *"unstable requirements and constraints based upon ill-defined environmental contexts"* (p. 81): This is true for LA, because learning scenarios very much depend on their actors, their goals and available resources, which also change with each new run. Furthermore, also the introduction of LA into learning might further change the environment and the stakeholders' perceptions of learning.

- *“complex interactions among subcomponents of the problem and its solution”* (p. 81): As discussions in the following chapters will show, LA stakeholders have conflicting interests. The design of a LA tool is therefore an attempt of finding a good solution, which is actually a reasonable compromise. Therefore, each design decision influences several other aspects of the overall situation.
- *“inherent flexibility to change design processes as well as design artifacts (i.e., malleable processes and artifacts)”* (p. 81): The effects LA have on TEL are hard to predict unless they are tested in real world scenarios. This might also lead to the necessity to perform radical changes during the design process. Design processes, which have been carried out independently with the same goals in mind, might still lead to different results because of their different contexts. It might be necessary to change the methodology based on newly gained knowledge of the problem domain.
- *“critical dependence upon human cognitive abilities (e.g., creativity) to produce effective solutions”* (p. 81): LA systems are decision support systems for humans, who need to interpret and act upon the analysis results in the context of teaching and learning.
- *“critical dependence upon human social abilities (e.g., teamwork) to produce effective solutions”* (p. 81): LA tools are dependent upon user-centered design, including diverse stakeholders during the whole design process.

3.2 Research Guidelines

The seven design-science research guidelines (presented in Table 2) are based on the fundamental assumption “*that knowledge and understanding of a design problem and its solution are acquired in the building and application of an artifact*” (Hevner et al. (2004), p. 82).

The first guideline ‘Design as an Artifact’ addresses the outcome of a design-science research project: a purposeful IT artifact, which can be applied to the problem domain. In the context of this work, the outcomes of the research project are: an IT artifact, namely eLAT (see chapter 6), and related ARLA models (see chapter 5), specifications, and guidelines that can be used and build upon by future research regarding similar problem domains (chapter 8).

The second guideline ‘Problem Relevance’ focuses on change and context. More precisely, the artifacts are supposed to overcome specific problems – the difference between a goal and a current state (Hevner et al. 2004), while being relevant for a certain target group. This work’s target group comprises ‘educators’ – or in other words ‘teachers’ – in higher education. Based on the problem, which has been specified in chapter 1, the main goal is to support the improvement of virtual teaching and learning scenarios and the personal development of technology-related teaching skills with the methodology of AR, and initiated by LA.

The third guideline 'Design Evaluation' emphasizes the necessity to integrate the new artifact (or early prototypes) in its intended context, in order to evaluate its impact. This requires appropriate methods for data collection and analysis. Evaluation results are fed back into the redesign of the artifact until "*it satisfies the requirements and constraints of the problem it was meant to solve*" (Hevner et al. (2004), p. 85). According to Hevner et al. (2004), design evaluation methods can be categorized into observational, analytical, experimental, testing, as well as descriptive methods. The selection of methods depends on the problem and the designed artifact. E.g., the following methods have been important for this work: method triangulation, literature reviews, focus groups with different stakeholders, surveys, interviews, and prototype evaluations within field studies, regarding usability and impact. Suitable combinations of these methods – whereby the choice of methods depended upon the respective evaluation goals – have evaluated each prototype that was developed in the context of this work.

The fourth guideline 'Research Contributions' determines that the research must provide clear contribution, regarding the design artifact, foundations, and/or methodologies, and solving a previously unsolved problem. These contributions are listed in chapter 1.

The fifth guideline 'Research Rigor' refers to thoroughly conducted, appropriate data collection and usage of analysis techniques, with regard to the relevance to the problem domain. The main goal is to estimate how well a solution works, rather than why (Hevner et al. 2004). This work chose mainly qualitative methods (e.g., semi-structured interviews and user tests with pilot users) to generate understanding from the data, which was collected for usability as well as for impact evaluation. So, there was a focus on evaluating 'how' a specific prototype worked. However, the study also investigated 'why' a prototype had impact on users and found influencing factors. Several data collection and analysis phases proceeded simultaneously and informed each other to tackle the complexity of the research problem.

The sixth guideline 'Design as a Search Process' highlights the iterative process. Starting out with simplified sub problems, prototypes may evolve step by step by eliminating their deficiencies. This enables researchers to increase their knowledge on realistic goals, constraints, and forces on the solution space. The goal is to find a satisfactory solution (Hevner et al. 2004). By implementing iterative design and evaluation cycle, each preliminary outcome of evaluations of prototype stages in the work at hand could be used in subsequent steps of the research project. Furthermore, factors of influence in real world environments that are important for applicability were detected. Therefore, it was possible to closely examine the complexity of the problem domain and develop an appropriate model for the solution.

The quality of the research process is measured by comparing it to related work. Thus, the last guideline 'Communication of Research' is essential for building a general research knowledge base. Studies of design science have to be repeatable and their outcomes must be presented to a wider audience. Therefore, outcomes of this work have been and are continuously presented and discussed in well-respected conferences and journals related to the research fields of LA.

Table 2. Design-science research guidelines. Source, Hevner et al. (2004).

Guideline	Description
Guideline 1: **Design as an Artifact**	Design-science research must produce a viable artifact in the form of a construct, a model, a method, or an instantiation.
Guideline 2: **Problem Relevance**	The objective of design-science research is to develop technology-based solutions to important and relevant business problems.
Guideline 3: **Design Evaluation**	The utility, quality, and efficacy of a design artifact must be rigorously demonstrated via well-executed evaluation methods.
Guideline 4: **Research Contributions**	Effective design-science research must provide clear and verifiable contributions in the areas of the design artifact, design foundations, and/or design methodologies.
Guideline 5: **Research Rigor**	Design-science research relies upon the application of rigorous methods in both the construction and evaluation of the design artifact.
Guideline 6: **Design as a Search Process**	The search for an effective artifact requires utilizing available means to reach desired ends while satisfying laws in the problem environment.
Guideline 7: **Communication of Research**	Design-science research must be presented effectively both to technology-oriented as well as management-oriented audiences.

This chapter presented the fundamental research paradigm, which is the basis for this work. The following chapters present and discuss the research process and results in terms of the seven guidelines, presented above.

4 FUNDAMENTALS

LA aims to facilitate awareness and reflection and to give appropriate information for decision making with respect to modifications of teaching concepts for the purpose of improvement. This chapter defines relevant terms and gives an overview on theories and research fields. Each topic is presented and examined briefly from the perspective of this work's goals.

4.1 Awareness and Reflection

Educators need to be aware of the needs, characteristics, learning status, and performances of their students, in order to reflect on and regulate their teaching. The next sections introduce the terms 'awareness', 'reflection', and 'action research' in more detail, because their meaning is substantial for understanding the following discussions.

4.1.1 Awareness

Synonyms for 'awareness' are, e.g., alertness, attentiveness, comprehension, consciousness, enlightenment, perception, or understanding (see, e.g., Thesaurus.com (2013)). Although, if someone is aware of something, it does not necessarily imply that he or she understands it. The opposite (antonyms) of awareness are, e.g., ignorance or unconsciousness.

In the context of this work, awareness is understood as a conscious state of mind that represents our ability to perceive the status of the environment in which we operate and plan our future actions. Our senses and perceptual systems help us in being aware of several things at once. This enables us to decide about our next moves for reaching our goals. Someone, who is more aware of the important aspects of a situation, might be able to perform better than others.

Awareness can be supported by technical means for successfully conducting tasks, such as driving a car. A car is a complex artifact. It is very important that drivers are aware of the state of their cars, especially if something is not working properly. Not only problems, but also everyday situations, such as running out of gas, need to come to the awareness of the persons inside a car in due time, since finding a gas station might take a while.

Dourish and Bellotti (1992), who studied awareness and coordination in shared workspaces, defined awareness as "*an understanding of the activities of others, which provides a context for your own activity*". Research on awareness in the context of TEL has focused on students, i.e., the connections between learning and awareness. E.g., researchers study diverse features in learning environments to improve awareness of the online states of fellow students and, hence, increase communication and collaboration among learners (Mochizuki et al. 2007). Repeated workshops on awareness and reflection in TEL have also demonstrated interest in the field (Moore et al. 2012). Whilst awareness is important for learning, it is also indispensable for teaching. A passion for teaching paired with awareness marks great teachers (Smoot 2013). The so called 'third ear' might be an important meta-level of thinking for teachers, which is important for self-reflecting on their own and their students' behaviors, as well as the structure of the content provided within a learning environment. Therefore, awareness is an inevitable pre-condition for reflection.

4.1.2 Reflection

The term 'reflection' has several meanings, depending on the context. It might name, e.g., a mirror image or the abilities of a computer program (Wikipedia 2013b). In the context of this thesis, reflection is referring to the ability of humans to think about internal and external events. Related terms that describe the concept of reflection are, e.g., consideration, cogitation, brainwork, study, observation, or speculation (Thesaurus.com 2013b). Atkins and Murphy (1993) conducted a review of the literature on reflection and concluded that only few definitions exist; e.g., Boud, Keogh, and Walker (1985) defined learning through reflection as "*those intellectual and affective activities in which individuals engage to explore their experiences in order to lead to new understandings and appreciations*" (p. 19). For the process of reflection, three key stages have been identified by Atkins and Murphy (1993):

- *Awareness of uncomfortable feelings and thoughts*: This stage is triggered by an experience of surprise or a stage of inner discomfort, grounded in the realization that ones knowledge is not sufficient to explain a situation.
- *Critical analysis of feelings and knowledge*: Based on the uncomfortable feelings, a person starts examing existing and new knowledge by exploring the situation, in order to feel comfortable again.
- *New perspective*: The outcome of reflection is a perspective transformation, which can be called learning and might lead to changes in behavior.

Atkins and Murphy (1993) conclude: "*Reflection, therefore, must involve the self and must lead to a changed perspective*" (p. 1191).

There are two types: reflection-in-action and reflection-on-action (Atkins and Murphy 1993). Reflection-in-action occurs during an activity and a person might not be aware of the knowledge that has been applied since it is based on intuition. Reflection-on-action is consciously performed after an experience to explore it in more detail. By fostering reflection-on-action both verbally in interviews and in writing reflective diaries, it can be used make the process of reflection more explicit (Atkins and Murphy 1993).

Current research around the use of LA for awareness and self-reflection by teachers and learners, e.g., shows that technology may provide more transparency in social interactions and opportunities to reflect on activities (Santos, Verbert, and Duval 2012). Furthermore, in order to foster awareness and reflection about cognitive and meta-cognitive learning activities, Nussbaumer et al. (2012) use LA. They aim at supporting students in self-monitoring their usage of widget bundles in the European research project ROLE, which provides learners with widget-based personal learning environments. Tabuenca et al. (2012) researched on using reflection amplifiers in form of daily questionnaires sent via text messages to students' smartphones to stimulate "*the opening up of and the reflection upon learning activities, contexts and channels*" (p. 12). Verpoorten, Westera, and Specht (2012) used three kinds of reflection triggers. These are prompts included with learning materials that asked learners to compare their learning experience to a larger context (e.g., activities of peers), rate their mastery of a page, or comment on a certain aspect of their learning.

4.2 Educational Action Research

AR is a reflective practice. It evolved as a method for practitioners to take responsibility for their own situations, e.g. in workplaces or social environments, by systematically and iteratively striving for improvements. Hence, AR is subjective. According to Kromrey (2009), it aims not at creating universal theories, but at using its subjective dimension to influence the research subject for specific changes. Regarding the educational context, AR has been discussed and used for the professional development of teaching skills (Altrichter, Posch, and Somekh 2005). Thereby, awareness and reflection play an important role. Berg (2001a) states that " *[...] action research is one of the few research approaches that embrace principles of participation and reflection, and empowerment and emancipation of people and groups interested in improving their social situation or condition.*" (p. 178).

While AR is seen as an important method in the international context, it has been the topic of controversial debates in German-speaking countries, as discussed by Altrichter and Gstettner (1993). Nevertheless, afresh interest in educational action research (EAR) with regard to learning designs of TEL or similar approaches is observable (e.g., Mor and Mogilevsky (2013)).

Many different terms refer to concepts similar to AR. It does not have one but many widely accepted definitions (Altrichter et al. 2002), as the next section explains.

4.2.1 Related Terms and Theories

Generalizations of results from traditional educational research have their limitations and do often fail at telling individual teachers what will work best in a particular situation with a specific group of students (Hinchey 2008). AR can be a solution here because it seeks local, rather than universal solutions (p.29). There are diverse views on this method, which led to a variety of different terms that more or less relate to AR. Some of these will shortly be discussed in the following to give an impression about the 'action research family'[2].

- *Participatory AR* in the context of education refers to AR activities that involve several different stakeholders. The main goal is to change schools, but also society at large.
- *Teacher research* or *teacher inquiry* refers to similar projects, but highlights the role of the teacher, who is responsible for enhancing the quality of action. It is focused on developing reflection on professional action in the context of practice itself. An advantage of teacher research is that the teachers have a sense of control of the research because they choose to examine their teaching practice for their own and their students' benefit. A limitation is that teachers, who already have lots of responsibilities, might view the research activity as an additional burden because they need to find time for collecting and analyzing data.
- *Collaborative action research* is supposed to involve several persons (researchers) working together for the trustworthiness of their research results. There are still some variations of collaborative effort within projects. E.g., a collaborative AR group might concentrate on answering several questions concerning one individual classroom. Alternatively, they could explore the same question in multiple classrooms.
- *Practical action research* focuses on local, practical problems. The purpose is to help teachers to find ways to affect change and systematically generate individual 'craft knowledge', instead of relying only on instincts. Hence, practical AR supports professional development.
- *Emancipatory action research* has more ambitious goals, seeking to change society at a whole. A main perspective is to show and overcome habits that have been unconsciously accepted. Therefore, everything should be questioned.

As written by Hinchey (2008), the main differences in these terms are based on slightly varying answers to the core questions of 'who?' is doing AR 'for what

[2] The selection is based on Hinchey (2008).

purpose?'. This works understanding of AR is close to the definition of 'teacher research/inquiry', whereby an individual teacher or a group of teachers strives to improve his, her, or their course regarding particular issues. Altrichter et al. (2002) provide a working definition, which describes aspects of a situation in which AR is occurring (see Table 3).

Table 3. Working definition of AR. Source, Altrichter et al. (2002).

If yours is a situation of action research

- people reflect on and improve (or develop) their *own* work and their *own* situations
- by tightly inter-linking their reflection and action; and
- also making their experience public not only to other participants but also to other persons interested in and concerned about the work and the situation, i.e. their (public) theories and practices of the work and the situation;

and if yours is a situation in which there is increasingly

- data-gathering by participants themselves (or with the help of others) in relation to their own questions;
- participation (in problem-posing and in answering questions) in decision-making;
- power-sharing and the relative suspension of hierarchical ways of working towards industrial democracy;
- collaboration among members of the group as a "critical community";
- self-reflection, self-evaluation and self-management by autonomous and responsible persons and groups;
- learning progressively (and publicly) by doing and by making mistakes in a "self-reflective spiral" of planning, acting, observing, reflecting, replanning, etc.;
- reflection which supports the idea of the "(self-)reflective practitioner";

then

yours is a situation in which action research is occurring

The next section highlights the key characteristics, which are inherent in most AR approaches.

4.2.2 Key Characteristics

AR is a method for reflective teaching practice that enables and guides teachers to investigate and evaluate their work (Altrichter, Posch, and Somekh 2005). Hinchey defines AR as "*a process of systematic inquiry, usually cyclical, conducted by those inside a community rather than outside experts; its goal is to identify action that will generate improvement the researchers believe important*" (Hinchey 2008). A key property of AR is that „*[a]ction research starts from practical questions arising from everyday educational work*" (Altrichter, Posch, and Somekh 2005, p. 5). This is supposed to further develop existing situations and gain knowledge about everyday activities. AR aims to be compatible with institutional values, working conditions, and it aims to contribute to its further development and improvement. Thereby, simple methods and strategies, which balance costs and benefit, are used.

Table 4. An example of a non-linear AR process. Source, Hinchey (2008).

"For example, a teacher researcher might plan to analyze one marking period of a student's writing. However, after collecting that data and beginning analysis, the teacher might sense a pattern but want more data to substantiate it. At that point, he might interrupt analyzing to collect more data, modifying the original plan by adding work from a second marking period." (Hinchey, 2008, p. 52)

There are a few key characteristics that are true for most AR projects. Regardless of how they are named (see p. 38), they all involve some core activities, which appear repeatedly – not necessarily chronologically (as demonstrated in Table 4) – in a flexible, cyclic process (Hinchey 2008):

- Developing a question
- Formulating a research plan
- Systematically collecting data
- Analyzing the data
- Developing and implementing an action plan
- Recording the project in writing

Additionally, several models suggest to share the results of action research with others (Hinchey 2008).

The AR steps 'systematically collecting data' and 'analyzing the data', are most relevant in the context of this work because LA can automate parts of these tasks and make them more efficient (see section 4.5). Action researchers can collect data form a variety of different sources. E.g., Hinchey lists:

- Documents and artifacts
- Journals

- Field notes
- Interviews and focus groups
- Surveys
- Audiotapes, videotapes, photos

It is notable that these data sources are mostly qualitative, beside surveys, which can be quantitative, qualitative, or both. Collecting and comparing multiple types of data (called 'data triangulation') over a sufficient length of time is supposed to minimize ambiguity in findings. Credibility is increased, if the same information appears in all sources (Hinchey 2008).

TEL scenarios offer additional possibilities for collecting data; e.g., teachers can also base their analysis on automatically collected logging data or meta-data, which can be extracted from VLEs. These kinds of data are also an important source for LA. The combination of all data promises to deliver a more holistic picture about learning processes.

4.3 Analytics in Education

Answers to the question 'What do you think of, when you hear the term learning analytics?' are diverse. Some people interpret the meaning of 'learning analytics' as 'learning about analytics', while others describe it as 'analyzing the process of learning' or 'analyzing the way people learn', or 'a method to improve learning'. All of these explanations are somehow correct, but need to be specified in more detail. It is true: researchers are still 'learning about analytics'. LA is an emerging research field, which gathers researchers at its own international conference 'Learning Analytics and Knowledge' (LAK) since February 2011 (SoLAR 2013a). Also, it is a hot topic of the Horizon Reports 2011 to 2013 (L. Johnson et al. 2011; L. Johnson, Adams, and Cummins 2012; L. Johnson et al. 2013). But how can LA be distinguished from analytics in general or from related research fields, which seem to be the same or rather similar at first glance? The following sections introduce research domains that are related to LA, in order to compare them to and differentiate them from LA subsequently.

4.3.1 Analytics in General

Analytics have a major impact on a variety of fields, industries, and events. For example, in the 2012 U.S. presidential elections big data and analytics played a crucial role (Shen 2013). Some statisticians predicted "*that Obama would prevail with close to 99 percent certainty based on aggregated poll data*" (Shen 2013) a few days before Election Day. Analytics was not only used for prediction, but also it was an integral part of Obama's political campaign. Large amounts of data were gathered and combined for systematically targeted promotions and fund raising, e.g., through picking specific stars as fund-raisers (Georg Clooney and Sarah Jessica Parker) to appeal to certain donors (Shen 2013).

Analytics also is commonly used in sports, e.g. basketball, for example to evaluate the performance of players (Cade 2012). Another important area for potential benefits of analytics is healthcare. For example, analytics can help in medical research to learn more about certain diseases.

LA reuses and remanufactures methods and technologies from established fields, like analytics, web analytics, business intelligence, and data mining, statistics, social network analysis and recommender systems (Chatti et al. 2012a). For distinguishing LA from other fields it is important to know them. Therefore, these fields are described briefly before looking into more closely related fields, like educational data mining, information visualization and academic analytics in the following sections (section 4.3.2 to 4.3.4):

- 'Analytics' *"is the discovery and communication of meaningful patterns in data*" (Wikipedia 2013c). 'Web analytics' is specifically concerned with analyzing the usage behavior and visitors profiles of web pages. Different metrics (key performance indicators), e.g., conversion rate, measure the effectiveness of web pages or marketing campaigns concerning specific goals. Important data sources are, e.g., log files, cookies, or client-based data derived from tiny one-pixel-graphics and JavaScript.
- 'Business Intelligence', also known as 'Management Information Systems', is a term that is mainly used in an economic context (Kemper 2004). The main goal of business intelligence systems is to assist with decision-making and planning based on accurate, current, and automatically generated business reports. Hence, common methods used are different forms of data processing and mining.
- 'Knowledge Discovery in Databases' and 'Data Mining' pursue the goal to generate patterns and new useful knowledge from databases in minimal time (Ester and Sander 2013). This field is closely related to 'statistics'. But data mining results may even be wrong from statistics point of view, since its methods are approximations that accept a certain loss of statistical correctness for runtime reasons. Related topics are also, e.g., data management, preprocessing, modeling, post-processing, and visualization.
- 'Social network analysis' provides tools to explore and analyze networks of persons based on graph-based visualizations (social network diagrams). This way, it supports the detection of relevant actors as well as connections between individuals and items. The interest in analyzing virtual social networks increases in recent years. "*This led to the development of different methods to study relationships between people, groups, organisations- and other knowledge-processing entities on the Web*" (D'Andrea, Ferri, and Grifoni 2009, p. 3).
- 'Recommender systems' is a research area within data mining and machine learning. It can help users discover information or items they

might not have found themselves. Therefore, recommender systems gather all kinds of data about users to analyze and to suggest products, context-specific resources, other users' profiles etc. (Zanker, Felfernig, and Friedrich 2011).

4.3.2 Educational Data Mining

In the research field of 'Educational Data Mining (EDM)', researchers are examining the development of methods for the generation of information from data of educational contexts. EDM is therefore the combination of data mining techniques with educational data. It aims to better understand students' learning processes and settings in which they learn (EDM 2013).

LA and EDM are quite similar regarding the analysis domain, data, processes, and objectives. Both fields focus on the educational domain, work with data originating from educational environments, and convert this data into relevant information with the aim of improving the learning process. However, the techniques used for LA can be quite different from those used in EDM. EDM basically focuses on the application of typical data mining techniques (i.e. clustering, classification, and association rule mining) to support teachers and students in analyzing the learning process. But EDM is mostly targeting the objectives of researchers, since it is more concerned with the development and evaluations of new data mining methods than with testing its usefulness in practical situations. In addition to data mining techniques, LA further includes other methods, such as statistics, visualization tools or social network analysis (SNA) techniques, and puts them into practice for studying their actual effectiveness on the improvement of teaching and learning. Therefore, further 'real world' issues, like data privacy, are important.

C. Romero and Ventura (2007), Baker and Yacef (2009), and Cristóbal Romero and Ventura (2010) provide excellent reviews of how EDM has developed in recent years as well as the major trends in EDM research up to 2009.

4.3.3 Information Visualization

Numerous studies have stated that large tables are not a particular user-friendly form of presenting LA information (Mazza and Dimitrova 2007; Ali et al. 2012; Cristóbal Romero, Ventura, and García 2008). For practical purposes, meaningful visualizations that are easy to interpret are required. Creating knowledge on the design of such visualizations is the objective of the research area 'information visualization (IV)'.

According to Card, Mackinlay, and Shneiderman (1999), information visualization is "*[t]he use of computer-supported, interactive, visual representations of abstract data to amplify cognition*" (p. 7). A dictionary defines visualization as "*the act or process of interpreting in visual terms or of putting into visible form*" (Merriam-Webster 2013). The first definition emphasizes the usage of tools to amplify cognition and the latter points out the activity of interpretation during the usage of visualizations. Hence, with the help of external visualizations users are "*using vision to think*", as the title of a famous book regarding IV suggests (Card, Mackinlay, and Shneiderman 1999). Another way to put it, according to Norman (1993), is that the invention of external aids, such as diagrams, has increased human memory, thought, and reasoning. Nevertheless, visualizations can also confuse their users. Therefore, it is important to understand, how they are used properly (Few 2007). Card, Mackinlay, and Shneiderman (1999) propose six ways in which visualizations can amplify cognition:

> *"(1) by increasing the memory and processing resources available to the user, (2) by reducing the search for information, (3) by using visual representations to enhance the detection of patterns, (4) by enabling perceptual inference operations, (5) by using perceptual attention mechanisms for monitoring, and (6) by encoding information in a manipulable medium*" (p. 16).

However, the main research question of the field of IV is how to convert data into interactive graphical representations, while preserving and emphasizing the intended meaning (Mazza 2004). An answer to this question "*depends on the nature of the data, the type of information to be represented and its use, but more consistently, it depends on the creativity of the designer of the graphical representation*" (Mazza 2004, p. 29).

Figure 2 shows how data can be mapped from raw data to visual form. It depicts a simple reference model for information visualization systems by Card, Mackinlay, and Shneiderman (1999). Data transformations convert raw data into data tables, visual mappings transform them into visual structures, and view transformations generate views through parameter selection (e.g., position, scaling, and clipping) (p. 17).

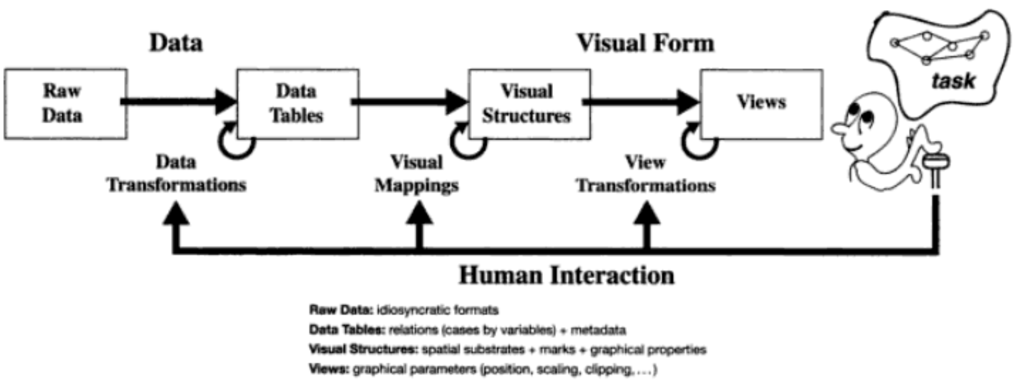

Figure 2. Visualization process model. Source, Card et al. (1999).

Findings from IV are important for presenting analytics outcomes because they can help to show information based on data and condensed in small spaces. Information visualizations are an integral part of LA, since they provide possibilities to engage users in monitoring and analyzing activities, while quickly conveying relevant information. Stephen Few (2006) emphasizes the need for good design principles for interactive dashboards and charts. This involves, knowing your audience and their goals, along with studying how visual perception works, and how to take advantage of this. "*When properly designed for effective visual communication, dashboards support a level of awareness—a picture of what's going on—that could never be stitched together from traditional reports.*" (Few 2007, p. 5) Since LA tools often are types of dashboards, his findings are especially relevant for LA.

4.3.4 Academic Analytics

Before this work goes into details on LA, a closely related and by definition overlapping term needs to be defined. According to J. Campbell and Oblinger (2007) academic analytics:

> *"[...] can help institutions address student success and accountability while better fulfilling their academic missions. Academic systems generate a wide array of data that can predict retention and graduation. Academic analytics marries that data with statistical techniques and predictive modeling to help faculty and advisors determine which students may face academic difficulty, allowing interventions to help them succeed.*" (Abstract)

By replacing 'academic' with 'learning' this definition could also be used for LA. Therefore, academic analytics, which was introduced by (Goldstein and Katz 2005), needs to be differentiated in more detail to be able to draw the fine line between both fields.

One way to do this is to have a look at the motivation behind academic analytics. Higher education institutions experience a growing demand for accountability and they have to document and present data on their accomplishments (J. Campbell and Oblinger 2007; J. P. Campbell, DeBlois, and Oblinger 2007), if they want to be capable of competing for students. This need is based on political and financial reasons. Example analytics implementations are predicting enrollment, student success, or student retention (J. P. Campbell, DeBlois, and Oblinger 2007). Against this background, academic analytics serve analogue purposes as business analytics or business intelligence.

Nonetheless, academic analytics serves the improvement of learning as well by pursuing the goals of increasing students success and graduation rates. Related projects use diverse sets of educational data, e.g., to predict students' risks status, allowing faculty and advisors to intervene (Arnold 2010; Tally 2009). While academic analytics is situated more at the level of higher education or even national decision making, LA is rather situated at a local level of teaching and learning in actual courses. It is concerned with the support of the actors of specific courses, like teachers and learners, by providing analytics for awareness, reflection, and action – as investigated by this thesis.

4.4 Learning Analytics

In the literature and on the web, several attempts to define LA can be found. The following section presents important definitions, further differentiates LA from other fields, describes models for the LA process, definitions of 'indicators', and elaborates on research challenges.

4.4.1 Definition

The potential of analytics is to "*help us to evaluate past actions and to estimate the potential of future actions, so to make better decisions and adopt more effective strategies as organisations or individuals*" (Cooper 2012, p. 3). In the case of LA, this purpose is oriented towards education. Some often cited LA definitions are presented in Table 5.

Although different in some details, these definitions share an emphasis on converting educational data into useful actions to foster learning. Furthermore, it is noticeable that these definitions do not limit LA to automatically conducted data analysis (Chatti et al. 2012a). But the majority of educational research assumes that "*learning analytics make use of pre-existing, machine-readable data, and that its techniques can be used to handle 'big data', large sets of data that would not be practicable to deal with manually.*" (Ferguson 2013)

4.4.2 Differentiation

As discussed above, LA is closely related to EDM, information visualization, and academic analytics (sections 4.3.2 to 4.3.4). Duval and Verbert (2012) also mention a connection between LA, big data, data mining, and information visualization:

> "*In this domain, huge data repositories collect traces of where people go, whom they interact with, what they buy, etc. Analytical applications then try to make sense of the data, either algorithmically through data mining techniques, or through information visualization techniques in visual analytics.*" (Duval and Verbert 2012)

Table 5. Definitions of LA.

Reference	**LA Definition**
1st Conference on LAK (2011) and also adopted by (SoLAR 2013b) and (Wikipedia 2013a)	„*Learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs*“
(Elias 2011)	„*Learning analytics is an emerging field in which sophisticated analytic tools are used to improve learning and education. It draws from, and is closely tied to, a series of other fields of study including business intelligence, web analytics, academic analytics, educational data mining, and action analytics.* “
(Siemens 2010)	„*Learning analytics is the use of intelligent data, learner-produced data, and analysis models to discover information and social connections, and to predict and advise on learning*"
EDUCAUSE Next Generation learning initiative; as cited in (Siemens 2010)	Learning analytics is “*the use of data and models to predict student progress and performance, and the ability to act on that information*”
Horizon Report 2011 (L. Johnson et al. 2011)	„*Learning analytics refers to the interpretation of a wide range of data produced by and gathered on behalf of students in order to assess academic progress, predict future performance, and spot potential issues. Data are collected from explicit student actions, such as completing assignments and taking exams, and from tacit actions, including online social interactions, extracurricular activities, posts on discussion forums, and other activities that are not directly assessed as part of the student’s educational progress. Analysis models that process and display the data assist faculty members and school personnel in interpretation. The goal of learning analytics is to enable teachers and schools to tailor educational opportunities to each student’s level of need and ability.*" (p. 28)

Ferguson (2013) explains the differences between EDM, LA, and academic analytics by assigning main research questions to each of these fields:

> "*The emergence of learning analytics as a field in its own right meant that there were now separate groupings focusing on each of the challenges driving analytics research.*
>
> - *Educational data mining focused on the technical challenge: How can we extract value from these big sets of learning-related data?*
> - *Learning analytics focused on the educational challenge: How can we optimize opportunities for online learning?*
> - *Academic analytics focused on the political/economic challenge: How can we substantially improve learning opportunities and educational results at national or international levels?*" (Ferguson (2013), p. 8)

Duval and Verbert (2012) see EDM as more focused on automating processes, whereby visualization is more about supporting users awareness and decision processes. They illustrate the distinction between EDM and information visualization with autonomous vehicles that could use algorithms to either "*steer the learner in the right direction*" or present dashboards that "*support people in being better drivers*" or rather "*help learners to be more aware of what they do, support self-reflection and enable sense making*".

The definition of LA in the Horizon Report of 2012 was quite similar to the definition of the Horizon Report 2011 (see Table 5). But the second part, concerning the objectives had been enhanced to state:

> "*The goal of learning analytics is to enable teachers and schools to tailor educational opportunities to each student's level of need and ability in close-to-real time. Learning analytics promises to harness the power of advances in data mining, interpretation, and modeling to improve understandings of teaching and learning, and to tailor education to individual students more effectively. Still in its early stages, learning analytics responds to calls for accountability on campuses and aims to leverage the vast amount of data produced by students in academic activities*". (Johnson, Adams, and Cummins, 2012, p. 26)

This citation highlights timeliness and efficiency of LA. It describes that LA makes use of advances in EDM.

It can be concluded that LA in general builds upon the research findings of several related fields to improve teaching and learning.

4.4.3 Process

Chatti et al. (2012a) presented a three-phase model for the LA process. As illustrated in Figure 3, it is an iterative cycle, which is generally carried out in the phases: (1) data collection and pre-processing, (2) analytics and action, and (3) post-processing.

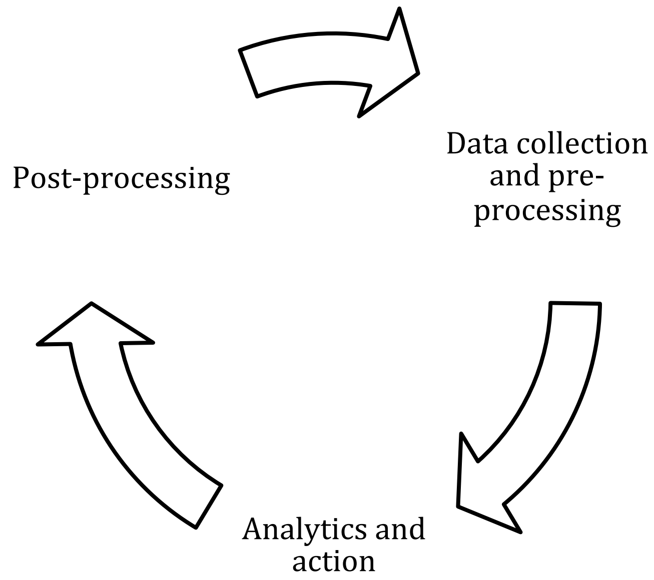

Figure 3. LA process. Source, Chatti et al. (2012a).

- *Data collection and pre-processing*: From a technical perspective, the first step is to collect data. This data comes from various educational environments and systems. Data aggregation and pre-processing is often necessary, since the collected data may be too large or include irrelevant information. Also, it might be helpful to transform the data into another format, which is required for a specific LA method.
- *Analytics and action*: The next step is to use LA methods for analyzing the data according to the goals of the users. Data can be explored in order to discover hidden patterns. Information visualization techniques are especially useful to help users understand analytics results based on large data sets more quickly. This can support them in their decisions and actions. Taking actions is the primary aim of the whole analytics process. These actions include monitoring, analysis, prediction, intervention, assessment, adaptation, personalization, recommendation, and reflection.
- *Post-processing*: The post-processing phase serves for the continuous improvement of the analytics exercise. Based on experiences of previous iterations, it may involve the collection of new data from additional data sources, refinement of the data set, identification of new indicators, modification of variables/filters, or selection of a whole new analytics method.

Elias (2011) compares the analytical process with a model of the 'knowledge continuum', which – according to her – was used by Baker (2007). It defines four units – data, information, knowledge, and wisdom – which are transferred from one into the other in a linear process (from 'data' to 'wisdom'). Hence, meaningless facts are transformed into knowledge that can be used purposefully.

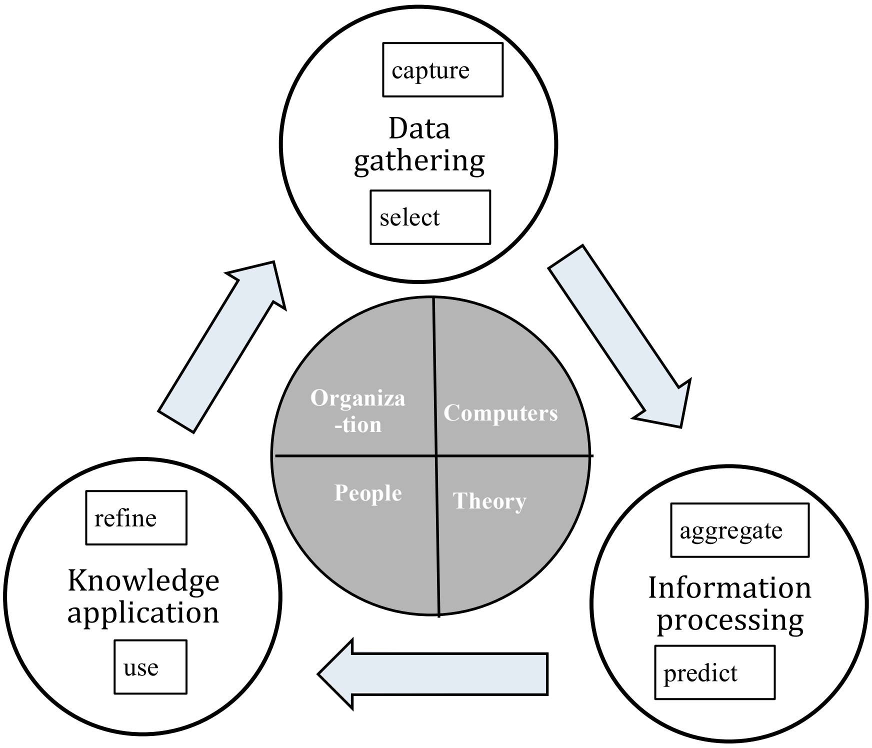

Figure 4. LA continuous improvement cycle. Adapted from Elias (2011).

Against this background, Elias's model also consists of a cycle:

- Data gathering: capture and select
- Information processing: aggregate and predict
- Knowledge application: use and refine (and share)

This process occurs as a combination of tools, actors, theories and organizations (see Figure 4). Elias points out the importance of people, especially when it comes to the implementation of theories and decision-making. Also, the characteristics of the participating organizations, their willingness to support the decisions and actions, and their leadership style play a crucial role (Elias 2011).

So, what is the impact of the LA cycle?

Verbert et al. (2013) distinguish four stages in their process model (see Figure 5).

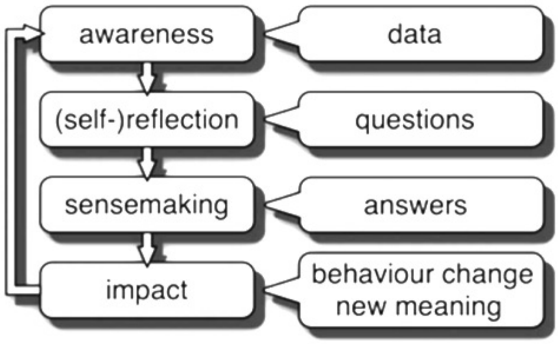

Figure 5. LA process. Source, Verbert et al. (2013).

The visualization of data, e.g., in activity streams, tabular overviews, or other visualizations, is supporting the stage of 'awareness'. In order to understand the data, the '(self-)reflection' stage focuses on users' questions, which are derived by reflection. In the 'sensemaking' stage, users try to find answer to the questions identified in the previous step. The goal, i.e., the impact, of the iteration is to induce new meaning or change behavior if necessary.

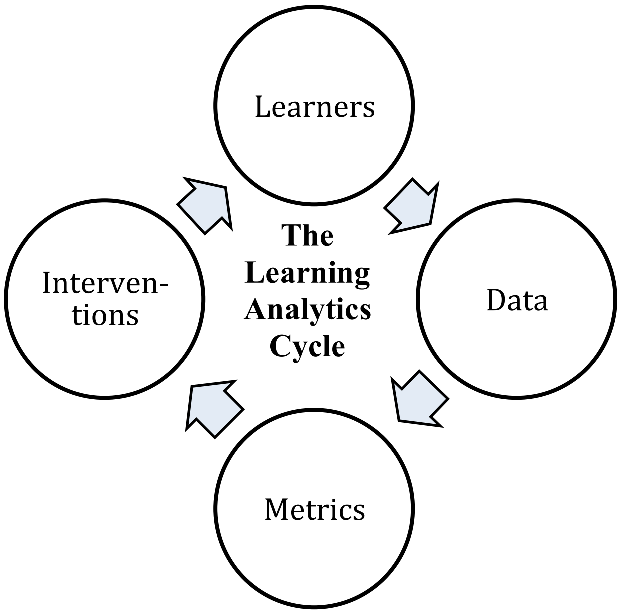

Figure 6. The LA cycle. Adapted from Clow (2012).

Clow (2012) proposes the 'learning analytics cycle' presented in Figure 6, which he developed based on Kolb's experiential learning cycle, Schön's work on reflective practice, and Laurillard's conversational framework (Kolb 1984; Schön 1984; Laurillard 2001). Clow's LA cycle starts with learners, followed by the step of capturing their data. The next step is processing it automatically or manually into metrics. Lastly, these metrics should be used for interventions that have an effect on learners. This intervention can be a dashboard, which shows the metrics directly to a learner, or a tutor, who contacts the learner personally (Clow 2012).

Within the work of this thesis, these descriptions have been revised and integrated into a new, more comprehensive model, which serves as a definition of LA processes with regard to AR. It is presented in chapter 5 and it was useful for evaluating the impact of LA in chapter 7 and verifying requirements in chapter 8.

4.4.4 Indicators

The concept of indicators is based on the idea of presenting results of automatic data analysis in small nuggets of information, which draw upon the concepts of information visualization for easier interpretation (May, George, and Prévôt 2011a; Dimitracopoulou 2008). One of the most preeminent features of indicators is their modularity. Hence, an important idea behind indicators is to enable personalization. LA users can be enabled to choose those indicators, which suit their purposes best, from sets of indicators.

Indicators can also be described as specific calculators with corresponding visualizations, tied to a specific question (A. L. Dyckhoff et al. 2012). For example, if a teacher's question is "*Are those students who practice with online exercise on a continually basis better in the final exam than students who do not use them*", the corresponding indicator could show a visualization that quickly facilitates a target-oriented data comparison of the different groups of students.

Glahn (2009) also used a concept of indicators. He introduced "*smart indicators*", which he defined as "*a context aware indicator system, which dynamically aligns data sources, data aggregation, and data presentation to the current context of a learner*" (Glahn 2009, p. 20). Whereby, according to Glahn (2009), *"[a]n indicator system is a system that informs a user on a status, on past activities or on events that have occurred in a context; and helps the user to orientate, organize or navigate in that context without recommending specific actions.*" (p. 65). Both definitions show that indicators can have different audiences and use different data sources and methods.

In the case of this work's goals the indicators' target group is mainly made up of teachers of a course. Indicators indicate certain facts about the users (students) and their usage and properties of a certain learning environment, relate them to other behaviors and properties, and visualize them appropriately.

Indicators are called 'indicators' because they just 'indicate' certain situations. An important notion of them is that they can lead different users to different conclusions. They depend on interpretations by users. Even wrong conclusions are possible. Therefore, the designs of indicators need careful considerations and several evaluative iterations. Furthermore, good indicator designs should be accompanied by guides and help documentation.

4.4.5 Research Challenges

What are the main challenges in the field? Several researchers have identified directions for future LA research. These challenges are concerned with educational theory, data integrity, implementation and design of tools, evaluation, and integration into everyday practice:

- *Connecting LA and educational theory*: Ferguson (2013) demands to build strong 'connections with the learning sciences'. On the one hand, learning science needs to be grounded in established theory. On the other hand, it can also influence and change the way we perceive processes of teaching, learning, and assessment (L. Johnson, Adams, and Cummins 2012). For example, LA can be a driver to keep on developing and refining learning models (L. Johnson, Adams, and Cummins 2012)
- *Data integrity*: In order to assure a complete, stable and nuanced picture of the learning process, L. Johnson, Adams, and Cummins (2012) ask for the usage of 'different data sources'. Working with a wide range of datasets is also seen as a future challenge by Ferguson (2013) and Chatti et al. (2012a). The question is how to aggregate and integrate raw data from multiple, heterogeneous sources, often available in different formats, to create a useful educational data set that reflects the distributed activities of the learner? Other related tasks are the 'sharing of data sets' (Duval and Verbert 2012) and support of 'mixed method approaches'. This means that not only different quantitative methods should be integrated to increase the robustness of research but also qualitative methods to answer the question of 'why' it is the way it is measured (Chatti et al. 2012a; A. L. Dyckhoff 2011). Furthermore, future research will be concerned with 'big data' (Chatti et al. 2012a); particularly, as soon as data from social media will become a source for analysis in education.
- *Design and implementation of processes and tools*: Elias (2011) denotes two tasks as key challenges of the LA research field. First, the 'development of processes and tools' for individual improvement of learning and teaching, and on the other hand, the 'integration' of these tools and methods in the teaching and learning of every day practice. This can be achieved by integrating them into the general learning environments of their users (L. Johnson, Adams, and Cummins 2012). As technical challenges 'real-time' (L. Johnson, Adams, and Cummins 2012) and 'performance' (Chatti et al. 2012a) as well as 'interoperability, scalability, and extensibility' should be taken into account (Chatti et al. 2012a). Of course, LA users represent 'different groups of stakeholders' with partly contradictory interests that have to be considered (Chatti et al. 2012a). The tools must also be 'adaptable' to individual needs (L.

Johnson, Adams, and Cummins 2012) and 'usable' for non-(data mining) experts (Chatti et al. 2012a). Guidelines and design patterns should be developed (Chatti et al. 2012a), such as a clear set of 'ethical guidelines' (Ferguson 2013; Chatti et al. 2012a).

- *Evaluation and Impact*: For the challenge of assessing the impact on learning, stated by Duval and Verbert (2012), the integration of LA into everyday practice of the different stakeholders is important (Chatti et al. 2012a). Evaluating the quality of analytics results in practice will also support the detection of 'meaningful learning traces' or 'pedagogically useful indicators', predictions, and recommendations (Chatti et al. 2012a).

4.5 Action Research and Learning Analytics

A literature review of the current situation showed that AR and LA have not yet been combined (see chapter 2). At first glance, the two approaches seem to be different, but a closer look at the goals associated with related AR or LA projects reveal similarities that call for a deeper analysis. While educational AR supports professional development by finding answers to practical questions, LA provides the tools for awareness and reflection, which also might facilitate professional development. Both approaches have the goals to foster reflection.[3]

Although the goals behind AR and LA are very similar, a difference can be seen in the initial trigger of related study projects. While AR projects usually start with a research question that arises from teaching practice (Altrichter, Posch, and Somekh 2005), LA projects often evolve based on observations made with regard to data, which has already been collected. While humans conduct AR, LA is often described as data-driven. Action researchers often use qualitative and quantitative methods to collect data and to generate a holistic picture of the learning situation. Current LA implementations mostly use different analytical methods from statistics and educational data mining to find information in large data sets, which are resulting from different kinds of information systems.

[3] This section is a revised and extended version of parts of A. L. Dyckhoff, Lukarov, Muslim, et al. (2013).

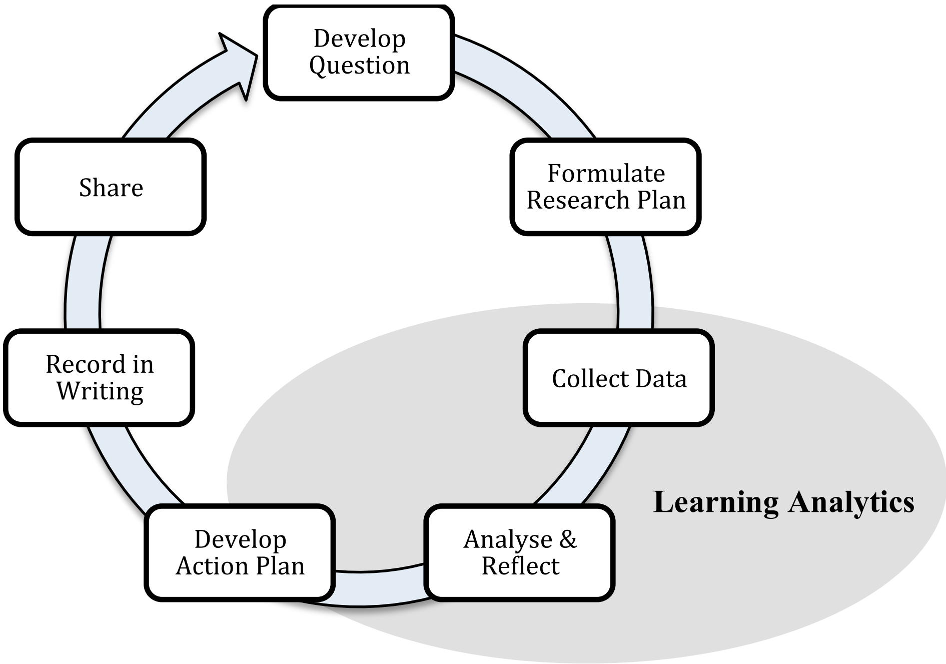

Figure 7. Current view of AR and LA.

Regarding the AR cycle and based on the interpretation of current LA definitions, certain LA steps can overlap with AR at the stages of data collection, analysis and reflection, and sometimes also in action planning or recommending activities to users (Figure 7).

In terms of LA, the creation of indicators so far has been controlled by and based on the (amounts of) data available in learning environments. Hence, the indicators might solely represent information that depends on the data sources used, e.g., by just making data visible that has been "*unseen, unnoticed, and therefore unactionable*" (Cator and Adams 2012).

But an important principle of AR is first to think about the questions that have to be answered before deciding about the methods and data sources (Hinchey 2008). Asking questions independently and putting aside the fact whether the necessary data is available or not, will lead to more and more relevant questions. This can provide more insightful information during the requirements analysis. This way, data and information gaps could be discovered, whose eliminations could help to improve the design of future LA tools and learning environments. These tools should not limit the possibilities of formulating own questions and pursuing individual goals.

Table 6 opposes key characteristics of AR to LA to show similarities as well as differences of both approaches; based on (Chatti et al. 2012a; Elias 2011; Hinchey 2008).

Table 6. Comparison of key characteristics of AR and LA.

	Action research (AR)	Learning analytics (LA)
Goals	Professional development, finding answers to practical questions, improvement of teaching, and social justice	Monitoring, analysis, prediction, intervention, assessment, feedback, adaption, personalization, recommendation, reflection and self-reflection
Process cycle	Develop a question – formulate research plan – collect data – analyze – develop and implement action plan – record project in writing – share	Data gathering (select, capture) – information processing (aggregate, report) – knowledge application (use, refine) and sharing
Driving factor	Human-driven: activities are centered around the person (group), who conduct the project	Data-driven: process is based on large amounts of data that promise to reveal new information
Advantages	Individual, perfectly fitting to a specific scenario, answers exactly the questions a teacher asks, open for all questions: What do I want to learn about my teaching? Methods of data collection can be adjusted creatively/accordingly	Standardized, general, suited for several scenarios, possibility to provide approved data analysis/visualization by research experts, developed for and well suited for TEL or distance learning, data privacy issues can be handled centrally
Drawbacks	Limited by time-constraints, a teacher's workload and AR know-how, data analysis error-prone due to human error, not optimized for TEL, data privacy and permissions need to be handled by the teachers	Limited by missing data, often restricted to quantitative data collection methods, interpretation difficulties, danger to answer only questions nobody is interested in, focused on questions like: What does the data tell us? Specific question cannot be studied
Mode	Manually	Automatically

Impact	Effecting reflection, motivation and teaching activities	Assumed influence on users' behaviors and reflective practice
Context knowledge	Knowledge about individual teaching situation (e.g., motives, teaching history, reasons)	Only data on teaching activities that have been recorded (e.g. log files, teacher journals, IMS learning design)
Instance	Single instance (or rather courses by one teacher)	Multiple instances of the same scenario possible
Methods	All kinds of qualitative and quantitative methods (e.g., surveys, interviews, video recording)	Limited to quantitative data collection methods (mostly data that can be logged automatically on different devices)

While AR is more focused on the human perspective, LA considers most aspects from the technical point of view. Both approaches have different advantages and disadvantages. This leads to the conclusion that joining both concepts can improve the impact of LA.

4.6 Conclusion

This chapter illustrated terms and theories, which are fundamental for the comprehension of the solution proposed in this thesis. Awareness and reflection are central terms in the main objectives of this work. Developers of LA tools need to know what awareness and reflection are, in order to design LA tools that have impact on the behavior of their users, namely to make them reflect newly gained knowledge.

Theories on educational AR go even a step farther. Thus, practitioners of AR should not only reflect about teaching, but also develop and adhere to action plans for improvement of learning.

This work focuses its research on the areas AR and LA regarding technology-enhanced learning in higher education. Hence, this chapter defined AR and LA and outlined their scope regarding other fields of analytics in education, which are closely related. Furthermore it compared AR and LA regarding immanent goals, process, driving factors, advantages and drawback, etc. It can be concluded that there are some differences, e.g. AR is human-driven and LA is seen as data-driven. However, many analogies can be found, e.g., regarding processes and objectives. Therefore, both approaches have been joined in the ARLA reference model, which is presented in the next chapter.

5 ARLA REFERENCE MODEL

The principles of AR processes are very similar to LA processes. This work discusses how both methods can be combined in a reference model.

Chatti et al. (2012a) developed a four-dimensional reference model for LA, which was used for the classification and analysis of different LA and EDM research projects. Such classifications should also consider AR principles. But the current LA reference model as well as the LA process models, described in section 4.4.3, lack distinct AR considerations. Therefore, a new model was developed in the context of this work.

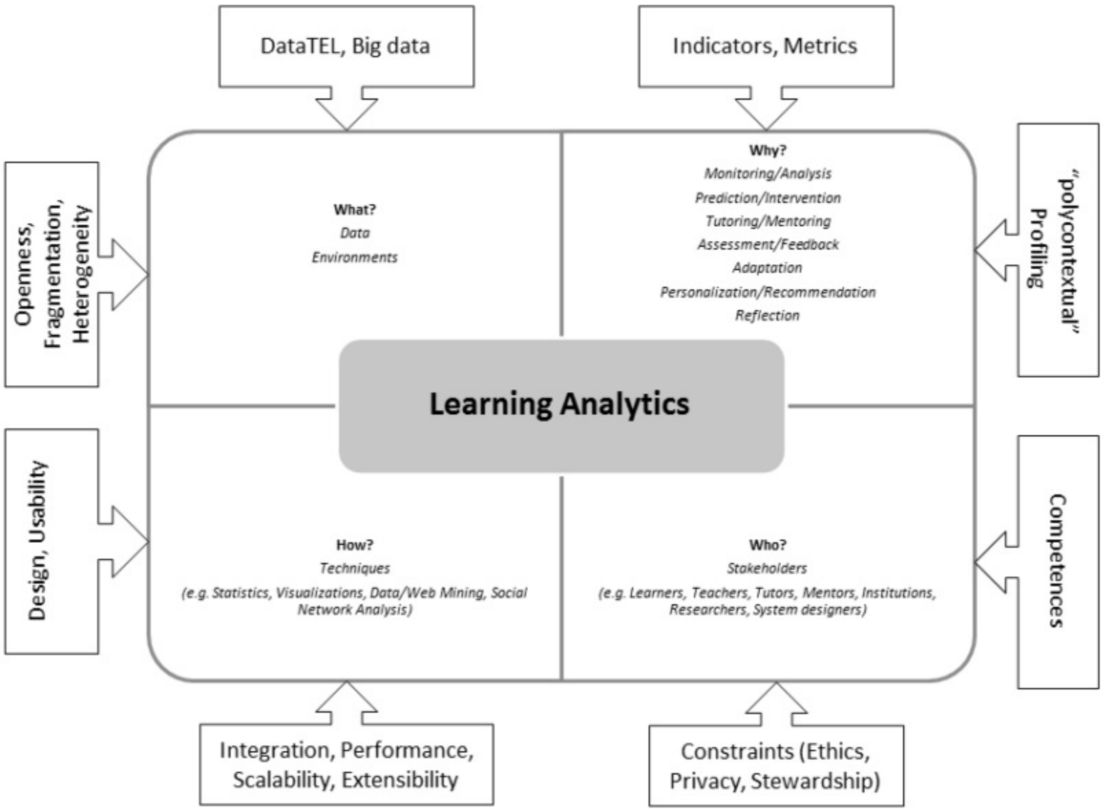

Figure 8. LA reference model. Source, Chatti et al. (2012a).

Chatti et al.'s LA reference model is structured in four main dimensions:

- What? (Data)
- Who? (Target group/Stakeholders)
- Why? (Goals)
- How? (Methods)

Regarding these dimensions, additionally several challenges and limitations, such as 'Design, Usability' or 'Constraints (Ethics, Privacy, Stewardship)', have been pointed out (see Figure 8).

At about the same time of the publication of our LA reference model (Chatti et al. 2012a), a design framework for LA was also published by Greller and Drachsler (2012) (see Figure 9), which is similar to the reference model described above. This model proposes six dimensions:

- Stakeholders
- Objectives
- Data
- Instruments
- External constraints
- Internal limitations

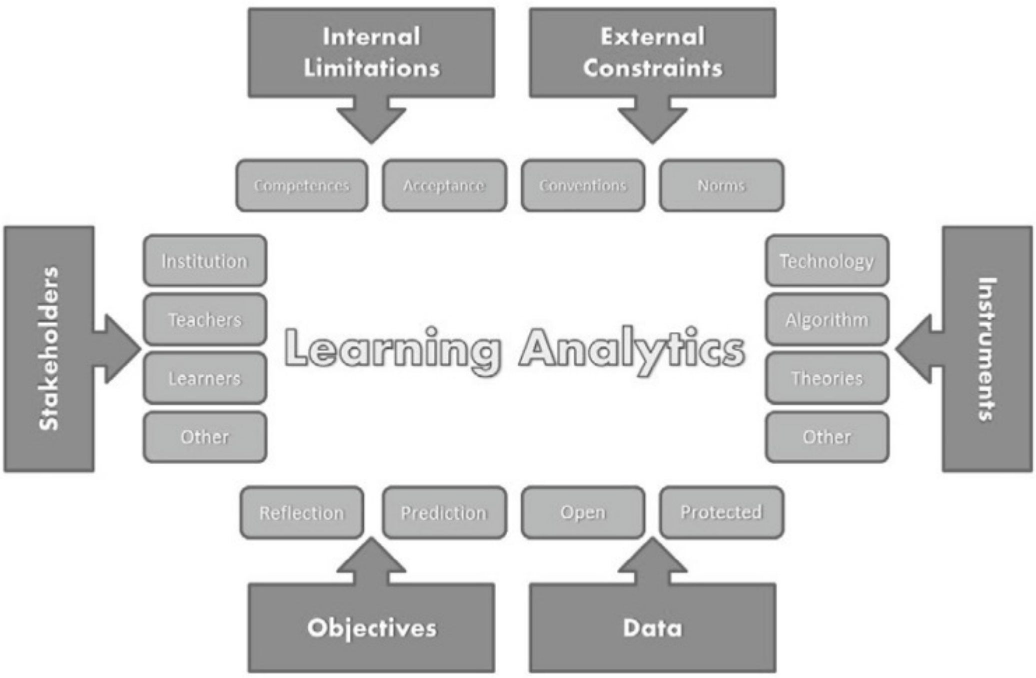

Figure 9. Design framework for LA. Source, Greller and Drachsler (2012).

The first four dimensions are comparable to the four dimensions of Chatti et al.'s (2012a) reference model. However, Greller and Drachsler (2012) highlight constraints and limitations by defining them as two separate dimensions. Chatti et al. (2012a) see these constraints as challenges or obstacles related to each of the four dimensions. While the dimensions regarding ‘stakeholders’, ‘data’, and ‘goals/objectives’ are almost the same in the two models, there is one noticeable difference between the ‘methods’-dimension of Chatti et al. (2012a) and the ‘instruments’-dimension of Greller and Drachsler (2012) (Figure 9); namely the inclusion of ‘theories’. ‘Theory’ refers to ‘pedagogical theory’ as an illustrative sample use case published by Greller and Drachsler (2012) suggests.

Both proposed models have been reviewed in context of the problem at hand, and their ideas have been integrated within the ARLA reference model, which is presented in the following paragraphs (see also Figure 10).

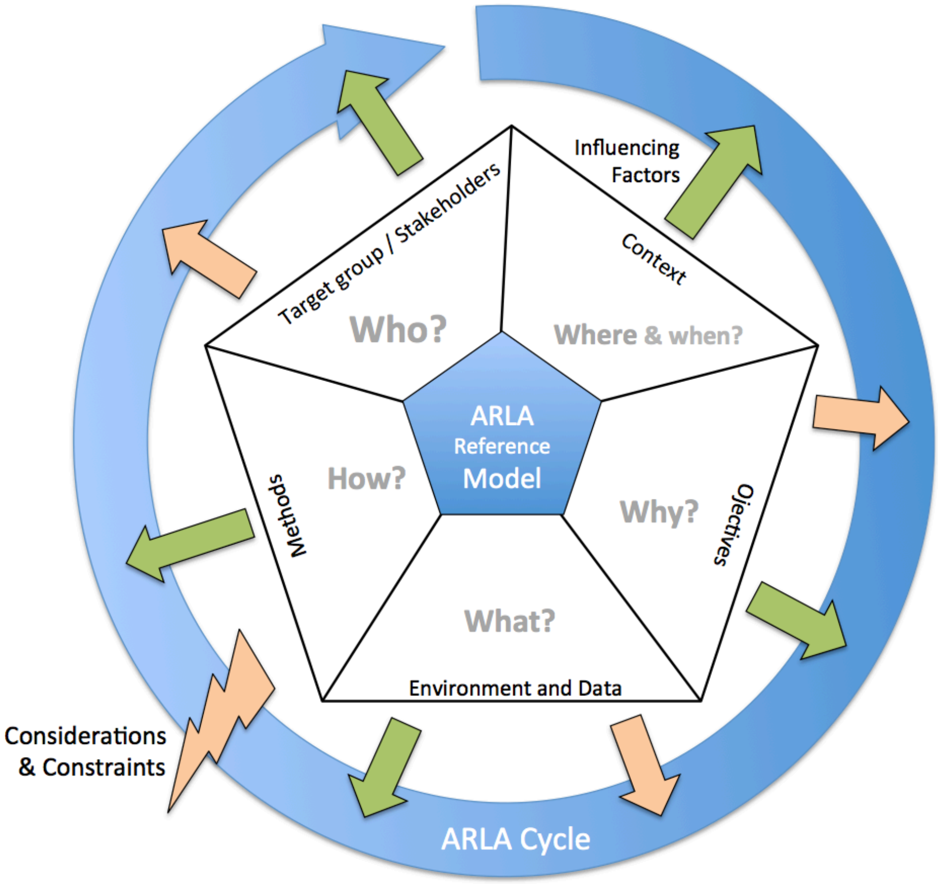

Figure 10. The ARLA reference model.

The new model takes the reference model of Chatti et al. (2012a) as a basis and adds further elements to it, which are relevant in the context of AR, and which have been proven to be important in the contexts of this work’s research findings.

Nevertheless, the model is similar to and also acknowledges Greller and Drachsler's (2012) approach.

5.1 ARLA Dimensions

The ARLA reference model consists of five dimensions, which will be discussed in the following sections (see Figure 10):

- Target group / Stakeholders (Who?)
- Context (Where and when?)
- Objectives (Why?)
- Environment and Data (What?)
- Methods (How?)

Each dimension is influenced by certain internal and external limitations and constraints. Success factors also need to be considered within the design of LA. The dimensions also influence each other, e.g., ‘objectives’ depend on ‘target groups’ (see Figure 11) and ‘context’ is related to ‘environment and data’.

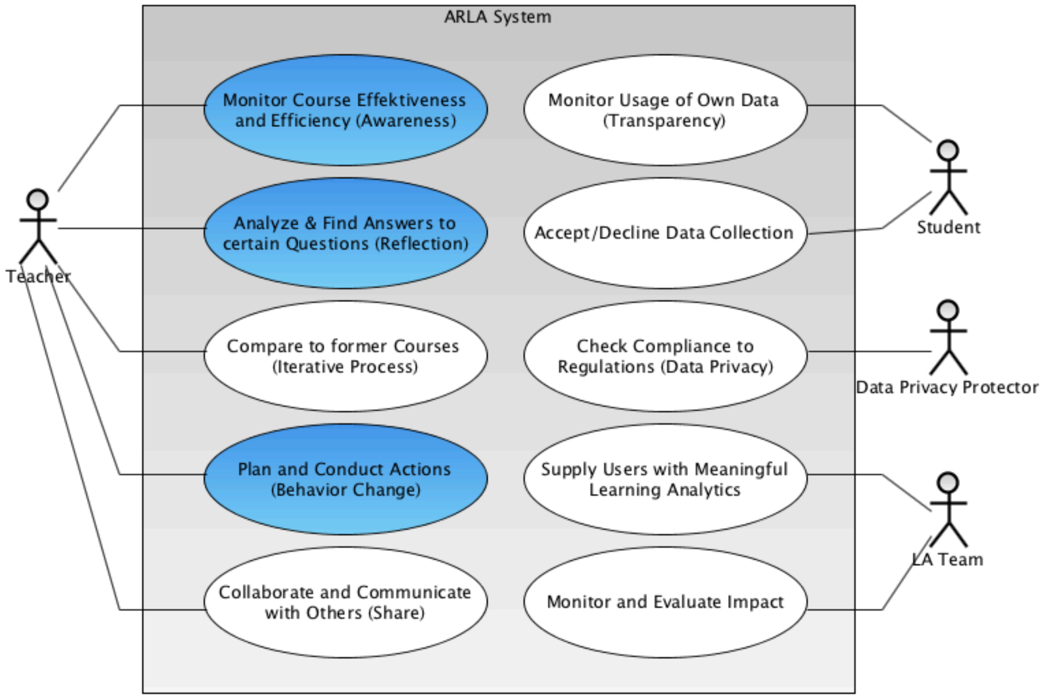

Figure 11. Use case diagram of the ARLA system.

5.1.1 Target group / Stakeholders (Who?)

The 'Who?' dimension is the most important dimension because the selection of a target group also influences all the other dimensions: where and when, why, what, as well as how? There are different groups that can benefit from LA. Target groups and stakeholders respectively are, for example – in addition to teachers, tutors and students, researchers – system designers, learning designers, administrators, and education institutions, represented by their decision makers. Also, parents might have an interest in LA. Table 7 and Figure 11 exemplary show this work's main target groups and stakeholders.

All these groups have different and sometimes conflicting expectations and perspectives. While students are interested in their own advancement and protection of their data, teachers want to know about the effectiveness of their learning designs for all or different groups of students. Decision makers (e.g., deans) in turn would like to receive the necessary pieces of information, which they need in order to make the right decisions at glance for entire departments or institutions.

To meet the requirements of different target groups, LA designers must clearly define their target audience and get to know it well. Potentially related, conflicting requirements must be identified and the resulting problems have to be solved together with users. LA projects should also give priority to implement simple user interfaces, which are understandable for both beginners and expert users.

Table 7. eLAT's primary target group (users) and further stakeholders

Primary target group	Teachers (e.g., professor, lecturer, teaching assistant) Tutor (student helper)
Stakeholders	Students Data privacy officers Administrator / System developers / IT support Dean / Rector

Although the target group is sometimes limited to one group – in the case of this work: teachers –, there is a certain necessity to take into account the external influences and interests of other groups. For example, students have specific interests in the extent to which their data will be used by teachers. The tool is likely to also affect the work of administrators, developers, as well as IT support staff. Furthermore, privacy laws make stipulations that must be adhered to.

Additionally, certain groups of stakeholders, such as learners, should not be seen as one homogenous group. In fact, each user, and certainly each student is different. For example, Kammerl and Pannarale (2007) discovered a relation between usage and field of study and between usage and self-assessed competency, whereby gender plays a role for self-assessment results.

Schulmeister discusses that "*cultural and ethnic differences between groups of students have a relevant effect on learning*" (Schulmeister 2004a). He suggested changing teaching in ways that take diversity into account and fostering open learning environments. The diversity of students is constituted by dimensions like motivation, cognition, learning styles, learning strategies, learning preferences, consciousness, and self reflection (Schulmeister 2004b). This gives a strong notion that LA should embrace this diversity, provide means to analyze it, and make it more visible.

5.1.2 Context (Where and When?)

The question of 'Where and When?' has not clearly been considered in the first publication of our LA reference model (Chatti et al. 2012a). It can be argued that it was included in the dimension 'What?'. This 'What?' dimension concentrated on the technical environments and data. The ARLA model highlights further context elements through an additional dimension, which is explained in the following paragraphs.

Especially in the context of AR, it is important to consider pedagogical contexts. This is also quite important, when implementing projects in practice in a certain time span. Institutions, or even courses, differ in many factors and often change as time passes by. Some institutions focus on distant learning, regardless of time and space. Others support TEL approaches, whereby traditional learning scenarios are enhanced by technology (blended learning).

An implementation of LA, which fulfills all requirements today, might be obsolete in a few years. Contexts change with regard to technologies and epistemologies. As mentioned above, Greller and Drachsler's (2012) model includes 'theories', which are also recognized by the ARLA model within the context of 'Where and When?'. These inherent theories influence the ways in which LA can have impact on awareness, reflection, action, and, hence, also on teaching and learning.

Multiple learning theories, such as behaviorism, cognitivism, constructivism, motivational and humanist theories, connectivism and LaaN theory, have influenced the ways in which we have looked upon on teaching in the past. The way teachers teach is based on their understanding of learning based on these theories and – as the evaluation results presented in section 7.2 show – their teaching very much influences the way they make use of LA. Therefore, the learning theories are part of the contexts of LA.

- *Behaviorism*: This learning theory views the human brain as a black box. It assumes that any behavior is caused by external stimuli and learning is defined as a change of behavior. Hence, learners are mostly seen as passive and supposed to be shaped through their environment. Methods of teaching are positive and negative reinforcement. Example theories related to behaviorism are, e.g., ‘classical conditioning’ or ‘operant conditioning’.

- *Cognitivism*: In contrast to behaviorism, cognitivism wants to understand what is in the mind. The brain is compared to a computer, which gathers, processes, and stores information. This processing is related to thinking. Cognitivism seeks to understand how learners learn and construct knowledge. Therefore, learning is defined as actively building or adapting mental schemata. Methods of teaching require learners to be active and think for themselves. Example theories related to cognitivism are, e.g., ‘cognitive load theory’ or ‘multimedia learning’.
- *Constructivism*: While cognitivism supports the assumption that knowledge is objective and can be learnt, constructivism views an individual’s knowledge as a subjective representation of the real world. Learning is viewed as a constructive and dialogical process. In it, learners interact with their environments and communicate with each other and the teacher, in order to link new information to their own prior knowledge. The main driver of learning is the attempt to understand ones’ experiences. Hence, important aspects of teaching and learning are personal experiences in authentic situations, where a certain learner can test and adjust hypotheses. Also, knowledge can be actively constructed by listening to the words of a good teacher. Example theories related to constructivism are, e.g., ‘cognitive apprenticeship’, ‘problem-based learning’ and ‘situated learning’.
- *Motivational and Humanist Theories*: These theories view learning as a personal act, which seeks to fulfill ones potential. Important aspects of learning are, e.g., motivation and interests. Teachers are seen as facilitators of learning. Their main task should be to promote and sustain motivation. A model for this is given though ‘attention, relevance, confidence, satisfaction (ARCS model)’.
- *Connectivism*: This theory emphasizes the importance of a learner’s access to external information. Connectivism defines learning as actionable knowledge. It happens not only internal, but also within social networks, organizations, and databases. Therefore, knowledge “*is distributed across a network of connections*” (Downes 2012). People can derive knowledge and competences from their connections to other humans and technical information sources. For this, they have to build networks of connections and acquire abilities for recognizing the need for new information as well as for distinguishing between relevant and irrelevant information (Siemens 2004).
- *LaaN Theory*: Chatti (2012) proposes the Learning as a Network (LaaN) theory. It builds upon connectivism, complexity theory, and douple-loop learning and views knowledge as a personal network from which knowledge can be drawn. This theory can serve as a theoretical framework for learning models that are based on personal learning environments (PLE). Based on LaaN, a 3P Learning Model shows how to achieve more

personalized, social, open, and dynamic learning situations, as opposed to centralized, top-down, and knowledge-push paradigms of traditional TEL models (Chatti, Jarke, and Specht 2010).

Most of the teaching methods, resulting from these theories, have their right to exist, since they comprise ideas that have been in some way or the other proven to induce learning. They have led to the creation of diverse and more or less successful learning scenarios, depending on when and how they have been applied. For example, for learning languages it can be helpful to repeatedly present words and follow teaching principles that have been introduced with behaviorism, whereas it is more difficult to teach how to implement solutions for complex problems. In this case, active involvement of learners is essential. It should be noted that contexts and target groups are very important for teaching and learning. We also need different scenarios for different contexts and levels of learners. This has been an important insight of constructivism. Learning scenarios in preschools, kindergartens, schools, higher education, or workplaces have different requirements. Learners become more mature and self-directed over time. Someone who needed more assistance from a teacher in the beginning of his or her educational career can become an independent, self-directed learner, who will depend less on the recommendations of a teacher but leverage his or her knowledge networks.

Even when one specific target group is chosen, there are different contexts for each person, using LA. For example, different teachers prefer different teaching methods. This diversity needs to be considered. In the case of this work, therefore, the AR methodology was selected as a suitable tool. It is suited for each individual situation because the participants themselves determine the LA goals, research questions, and methods used.

Table 8. eLAT's context.

Context (where and when?)	RWTH Aachen University in 2010-2013
Type	Higher Education (Bachelor / Master) International students
Approach	Blended learning / TEL
Learning theories / Course types	Diverse (depends on course objectives) / Lecture Seminar Exercise course Laboratory Thesis etc.

This work focuses on teaching and learning in a higher educational institution (see Table 8). Students in this context are presumably experienced, successful learners – otherwise, they would not have fulfilled the university's enrollment requirements. But still, in 2013 most of them were used to the teaching of fairly teacher-centered schools, when first arriving at a university. Also they come from different contexts and cultures, which increases the diversity among students of the same age. Successful students become more and more self-regulated learners during their studies at a university.

All of this needs and should be considered by educational implementations regarding university-wide TEL platforms. Especially, LA tools need to consider the contexts of their users by allowing for AR. Since these users know their contexts best, LA systems should provide them with possibilities to choose themselves, what best fits to their scenario. Furthermore, context is not only connected to pedagogical theory, but also to systems/environments, and data, as will be discussed in section 5.1.4.

5.1.3 Objectives (Why?)

The reasons behind the integration of LA into practice can vary. Chatti et al. (2012a) listed and explained possible objectives:

- Monitoring,
- Analysis,
- Prediction,
- Intervention,
- Tutoring / Mentoring,
- Assessment,
- Feedback,
- Adaptation,
- Personalization,
- Recommendation, and
- Reflection.

According to Greller and Drachsler (2012), possible objectives can be subsumed as "*reflection and prediction*".

This work adds the objectives '*awareness*', '*action*', and '*behavior change*' to complete this overall list. Therefore, the ARLA model highlights especially the following goals, but it also acknowledges the objectives mentioned above:

- *Monitoring and Awareness*: The act of supporting monitoring activities is supposed to help with decisions that different stakeholders have to make. But this activity is not the final goal. Monitoring, e.g. tracking students' activities, should lead to 'awareness', which is an important objective of this work and is discussed in section 4.1. It is the prerequisite for reflection.

- *Analysis and Reflection*: During the activity of monitoring data, one can detect surprising information or data constellations, which are hard to explain. This often leads to analysis activities. Such surprises, uncomfortable feelings and resulting analytical activities lead to 'awareness' and 'reflection' (see section 4.1.2). In these situations, users are motivated to dig deeper into the data compared to just monitoring it. While monitoring is rather receptive, analysis has a more active notion and demands higher involvement and reflective thinking. Therefore, analysis has a higher potential to create impact.
- *Action and Behavior Change*: The adequate presentation of data and information to users by LA is supposed to influence their way of thinking. With the help of analytics tools people can check their own behavior and achievements and compare it to others. This reflection is the basis for decisions on actions and improvement processes, which are then executed by constructive actions and changes of behavior. The systematic and intentional process of reflection and action is an AR cycle. It has been described in further detail in chapter 4.

Table 9. eLAT's objectives.

Objective (why?)	Awareness of students' behavior and diversity Reflection of teaching quality Action Research

Note that different objectives can be combined and specified, as the example in Table 9 and Figure 11 (section 5.1.1, p. 62) demonstrate. The goals of the project at hand have also been stated in chapter 1 by asking, how LA tools should be designed so that teachers are aware of the students' learning behavior and diversity, encouraged to reflect on the quality of their teaching, and inspired to explore and improve the quality of their teaching in terms of AR and LA.

5.1.4 Environments and Data (What?)

Universities are still unaccustomed to TEL, because it demands new development or change of existing didactical scenarios and learning cultures (Kerres et al. 2009). Many higher education institutions have established content management systems (CMS) or learning management systems (LMS), which are called virtual learning environments (VLE) in this thesis. The learning management system of RWTH Aachen University is L²P (Schroeder 2009). L²P was the main environmental context for eLAT implementations (Table 10).

VLEs are often learning platforms, which co-exist – more or less integrated – besides systems for the organization of education, e.g., for the management of grades and student profiles (Kerres et al. 2009). Most VLEs include several features for organizing teaching, like participant management, announcements and e-mails, literature and document libraries, wikis, and discussion boards. The most used functions have been related to distribution of information and resources from teachers to students. Therefore, Kerres et al. (2009) posed the question if current VLEs are really ‘learning platforms’ or if they only serve for distribution of content, while communication and collaboration among students occurs elsewhere. Chatti (2011) criticizes three main deficiencies of current TEL implementations: the general view of “*knowledge as a thing*” that brings forth a focus on content delivery, “*learning as a predetermined process*”, which is controlled by an institution, and “*TEL as a technology issue*” for increasing of efficiency rather than the effectiveness of learning with a one-size-fits-all approach. This demonstrates that VLEs are not independent from theory (section 5.1.2).

Table 10. eLAT's environment and data.

Environments	L²P
Data	Interaction protocols Metadata Student profiles/enrollment data Content/Resource Data Assessment/Performance Data

In order to better serve modern learning theories and acknowledge the rise of web 2.0 technologies, Kerres et al. (2009) suggest integrating LMS with personal learning environments (PLE) of students (for Kerres’s example, see Figure 12). Such VLEs are able to easily incorporate external systems, and news feeds from other websites in addition to own learning material repositories. Users have the choice regarding their tools for managing communication and group processes. These VLEs document learning processes and results automatically.

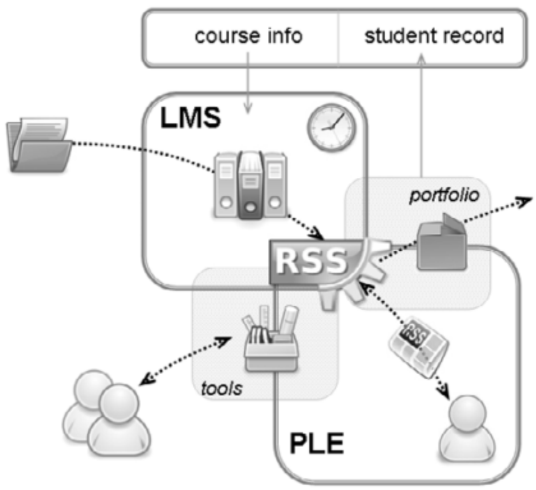

Figure 12. An integrated e-learning environment. Source, Kerres et al. (2009).

Based on this, Kerres et al. (2009) defined five central requirements for future VLEs:

1. *Assigning and orchestrating social roles and rights*: For example, the role ‘teacher’ could have the right to upload, link, edit, and delete resources for a course and a ‘student’ would be allowed to upload documents within a group workspace.
2. *Organize activities of the actors*: There are not only resources in a course, but also time schedules of learning activities. A VLE could organize or recommend certain sequences of learning activities. Also, it should track the users’ progress.
3. *Connection of learning materials*: VLEs should support the seamless integration of (sets of) external resources, without copying them into their own database or linking them repeatedly each semester for a new course. It could support the creation and management of meta-courses from which courses can inherit their content and structure.
4. *Provide meta-information for courses*: Courses often provide organizational information, like time schedules, participant lists, related courses, as well as, didactical information, such as, learning goals, course prerequisites, etc. This should not be copied but integrated from other systems, like university calendars.
5. *Document learning processes and results*: A VLE should support or integrate e-portfolios for its users, by tracking their learning traces and outcomes.

These requirements describe an abstract design for a future VLE, which is open and closely interlinked with students’ PLEs. A concrete example for an open VLE can be found with L²P, the learning and teaching platform of RWTH Aachen. Its upcoming version will be open for integration with other systems and oriented towards students’ needs and collaboration. Every user will be able to personalize his or her learning experience. This will be achieved though an app concept, personal dashboards, an app store, as well as APIs and web services, which will be available for all developers, who want to build additional features for L²P (Jakobs 2013).

If VLEs manage to adapt to changing educational contexts, they will remain important in higher education. But they need to change into the directions described above to support more open and collaborative learning scenarios. LA, which is using data from VLEs, can only be effectively used, if they consider the current technical facilities of VLEs. But for sustainability reasons, it should also be developed with respect to prospective technical advancements, e.g., regarding the openness of VLEs.

The following paragraphs are focused on different types and models of educational data as well as on standards and trends, since these are important for many LA projects. According to Chatti et al. (2012a), "*LA is a data-driven approach*" and an *"interesting question in LA is where the educational data comes from*" (p. 7). Educational data can be divided into the following categories:

- *Interaction protocols*: Log files are protocols, which are automatically created to store all or specific activities on a computer or server. Typically, all actions that could be relevant for later analysis, evaluation or auditing are recorded. Entries within a log file usually consist of an event/activity, an object/source regarding the activity, and a time stamp. Webservers often store, who performed an activity (via IP addresses). In other words, interaction logs are able to answer the question: 'Who has done what where at what time and for how long?'.
- *Metadata*: Metadata can be related to all kinds of objects in a learning environment. For example, it can give additional information regarding content or students, or it can describe aspects of a course's learning design. The standards described below provide ways to include metadata.
- *Student profiles/enrollment data*: Student data is a form of metadata. All educational institutions need to store information about enrolled students for the different purposes of organizing teaching, learning, and certification of learning outcomes. They need to be able to distinguish students from each other, contact them and keep records of their studies, as well as financial issues. Hence, they need the students' personal information, like names, IDs, current addresses, enrolled field of study, and their individual progress within a certain curriculum. Often, additional information is also stored, like gender, birth, and language, in order to contact specific groups of students.
- *Content/Resource Data*: Content data is all data that is created or uploaded by students or teachers. Most obvious, these are all kinds of documents or wiki pages. But it might also include text of discussion entries or survey questions and answers. Even data about the grades of students, which is stored in an e-learning system, could be interpreted as content. However, this work proposes assessment and evaluation data as separate categories.
- *Assessment/Performance Data*: This type of data refers to all kinds of records of performances of learners, such as grades regarding homework submissions, e-tests, or exams. This can be stored within local course grade books or by central examination offices. In the context of e-portfolios, assessment data could also refer to the outcomes and objects of learning processes, like the product of a homework submission, or the flow of the process of the learning activity itself.
- *Evaluation Data*: This type of data can be qualitative or quantitative, unstructured or structured. If evaluation data is collected with the help of technologies, very often the method of choice is to do a survey. Data types very much depend on the design of the evaluation method. In case of surveys, e.g., the collected data could be in form of free-text answers, but

also – and more easy to analyze by automatic means – tables of pre-defined answers that can be transformed into numbers with the help of coding schemes. Evaluation data can also contain results from ratings of resources or activities. Furthermore, data from social media platforms could be used to answer questions.

- *Qualitative Data:* With regard to AR, several qualitative data collection methods, such as collecting relevant artifacts or writing journals, have been mentioned in section 4.2.2.

There are also other types of educational data, which have not been mentioned above. For example, attendance or participation data, which some teachers collect to check attendance and participation rates in face-to-face classes. Table 10 shows which data is used within eLAT.

Data can also have standardized forms. Standards are formal documents that establish guidelines for different purposes: mainly economic benefit through interoperability of different systems or resources (Stracke 2010). The following standards or rather specifications are relevant for most TEL implementations:

- The Sharable Content Object Reference Model (SCORM) is a collection of existing standards and specifications (ADL 2013). It defines the exchange of information between a learning unit and a learning system.
- IEEE Learning Object Metadata (LOM) is a standard for metadata to describe learning objects. It was developed to facilitate the exchange, the search for, and use of learning objects.
- The IMS Learner Information Package (LIP) specification describes the structure and the creation of profiles. These include skills, characteristics, and other information about learners.
- IMS Learning Design (LD) is a formal modeling language for teaching processes. LD can describe the design of a learning unit explicitly and formally. Thus, a software-based interpretation is possible.
- Contextualized Attention Metadata (CAM) is a data format for logging activities of computer users, e.g., accessing a document or sending an e-mail (Schmitz, Wolpers, et al. 2009). CAM describes, "*which data objects attract the users' attention, which actions users perform with these objects and what the use contexts are*" (p. 1).

In future LA applications linked data will play an important role. Linked data is closely connected to the idea of a semantic web, which is supposed to enable users to find, share, and combine information more easily. Several techniques, like Resource Description Framework (RDF), Web Ontology Language (OWL), and Extensible Markup Language (XML), have been developed to serve this purpose. The key concept of linked data is to have an accessible "*web of data*", including relationships among data (W3C 2013). Thus, data can be explored more easily or – as Tim (Berners-Lee 2009) described it – "*With linked data, when you* *have some of it, you can find other, related, data.*" According to Berners-Lee (2009) linked data should have URIs as names for things, use HTTP URIs so that people can look up those names, provide useful information, using the standards (RDF*, SPARQL), and include links to other URIs, so that they can discover more things.

Linked data is also related to LA. For example, local data can be used together with reference data to inform recommendation mechanisms. However, depending on the queries searching through 'linked data', one might have a 'big data' problem.

The term '*big data*' has a high usage frequency related to the field of LA. It stands for "*datasets whose size is beyond the ability of typical database software tools to capture, store, manage and analyse*" (Manyika et al. 2011, p. 1). According to Wikipedia, big data is:

> "*a collection of data sets so large and complex that it becomes difficult to process using on-hand database management tools or traditional data processing applications*". Big data "*in many sectors today will range from a few dozen terabytes to multiple petabytes (thousands of terabytes)*" (Manyika et al. 2011, p. 1).

It includes structured data from databases as well as semi-structured and unstructured data, like multimedia and social media (Purcell 2013). In fact, educational institutions are handling growing sets of data, e.g., related to students' academic profiles or interactions with virtual learning environments. They seek to use these increasing amounts of data for the improvement of teaching and learning (having the opportunity for easily accessible information at the finger tip). A key driver for the research on the application of analytics tools is the question, how to extract value from the big sets of learning-related data (Ferguson 2013).

Educational institutions have large amounts of data, but do educational institutions have 'big data'? They do not, as long as they only analyze the data stored in their own databases. But they will have it in future teaching scenarios, if they strive to integrate social media, mobile, or sensor data in LA. Chatti et al. (2012a) state:

> *"As learning tools and resources are increasingly moving into the cloud, the challenge is how to aggregate and integrate raw data from multiple, heterogeneous sources, often available in different formats, to create a useful educational data set that reflects the distributed activities of the learner; thus leading to more precise and solid LA results. Furthermore, handling of "big data" is a technical challenge because efficient analytics methods and tools have to be implemented to deliver meaningful results without too much delay, so that stakeholders have the opportunity to act on newly gained information in time. Strategies and best practices on how*

to deal with the data volume have to be found and shared by the LA research community." (p. 8).

The most promising advantage of big data for education is its high potential to improve decision making processes (Manyika et al. 2011). A disadvantage is that principles, such as choosing a representative sample, are neglected. Boyd (2010) illustrates this by an example: "*You cannot analyze Facebook Friends lists and say that you've analyzed a person's social network. You haven't. You've analyzed their Facebook Friends list.*" Therefore, Boyd (2010) names five maxims related to big data:

1. Bigger Data are Not Always Better Data
2. Not All Data are Created Equal
3. What and Why are Different Questions
4. Be Careful of Your Interpretations
5. Just Because It is Accessible Doesn't Mean Using It is Ethical

LA tools need to consider technologies as well as different sources, types, and sizes of data, and these considerations should be based on the objectives that have been defined previously. Furthermore, new tool developments need to take into account established e-learning standards. For this work, an overall conclusion from this section on 'Environments and Data' is that it is important to think about what questions to ask and how to answer before deciding about appropriate data sets. Also, future data models need to be designed in an open way, in order to include new data, resulting from innovative questions.

5.1.5 Methods (How?)

In order to answer different questions, LA provides diverse techniques, which also can be mixed for reaching the objectives. According to Chatti et al. (2012a), statistics, information visualization, data mining, and social network analysis have received particular attention in literature in the last couple of years. Furthermore, Greller and Drachsler (2012) mention machine learning techniques or natural language processing.

The main challenges regarding the question 'how?' are to choose the right methods and design usable and useful interfaces for the specific stakeholders (see section 5.1.1) in LA. LA designers need to be aware that "*[c]ompeting methods, technologies and algorithms applied to the same set of data, will result in different outcomes, and thus may lead to different consequences in terms of decision making based on these outcomes.*" (Greller and Drachsler 2012, p. 9).

Chatti et al. (2012a) also highlight the importance of effective, real-time data exploration and integration in existing environments. Hence, "*performance, scalability, and extensibility should be taken into account*" (p. 13). At the same time, the methods need to be presented in usable interfaces for the intended target group. So, usability engineering is essential for creating LA tools, which fulfill the objectives.

We also need to design for AR. The best methods for automatic data processing and information visualization are useless, if the targeted audience does not invest time in using them for the benefit of teaching and learning. LA users need to take the time to monitor data, interpret it, draw (the right) conclusions, and act. An LA tool itself can be seen as an intervention method, which has the objective to have impact on a user. So, for a successful intervention, it is important when and how LA is integrated into the user's environment, how its design is appreciated by the user, how its design supports certain tasks, in order to facilitate AR processes, and how the user's tasks are supported by the system or related qualifications, in order to prevent misuse.

5.2 The ARLA Process

The ARLA model includes a process model of AR and LA activities. The ARLA process is an iterative cycle, which includes activities and effects of these activities on a users mindset. The following paragraphs argue how the process model was theoretically derived from comparing characteristical AR processes and different descriptions of LA processes.

5.2.1 Deduction from Theory

As compared to Figure 7, in Figure 13 the connection between AR and LA has been revised in this process model.

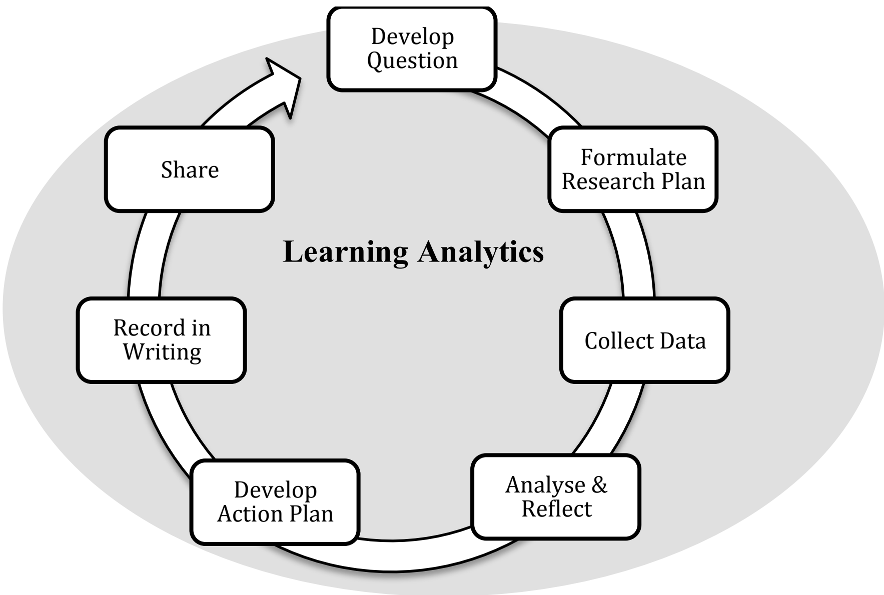

Figure 13. LA tools should support and enhance all steps of the AR cycle.

All steps of the AR cycle should be an integral part of LA. Therefore, LA should support personalization and the flexible development of questions per user. Instead of only relying on existing data collections, LA tools could include collection of data from additional sources, to avoid missing data and incomplete visualizations of learning processes. This requires LA tools to allow for the formulation or selection of questions that individual users want to answer. Also, the development of action plans, collaboration, and recording the project in writing could be supported. This might deliver data for LA related recommender systems, which recommend certain LA findings to other users. Basically all steps of the AR cycle should inform the design of LA tools. This could help users to think about what they are doing while they are doing it, especially, if LA tools are integrated into their normal working environments.

5.2.2 ARLA Process Model

Figure 14 presents the ARLA process model. It is a detailed view of the combination of AR cycle and LA process. It also considers the LA models of Chatti et al. (2012a), Elias (2011), Verbert et al. (2013), and Clow (2012) (see section 4.4.3).

The core process, depicted by the cycle at the center, consists of six main phases, which need to occur so that LA can have an impact on teaching and learning:

- Monitoring and analysis
- Inability to explain data
- Critical analysis and reflection
- Sense making and new perspective
- Analytics post and pre-processing
- Data selection, collection and pre-processing

Each phase can influence ones understanding and chain of thought. The bubbles represent the state of a user's mindset after each phase:

- Assumptions
- Unanswered questions
- Awareness
- Inner Discomfort / Surprise
- New Questions
- Answers
- Action Plan
- Impact

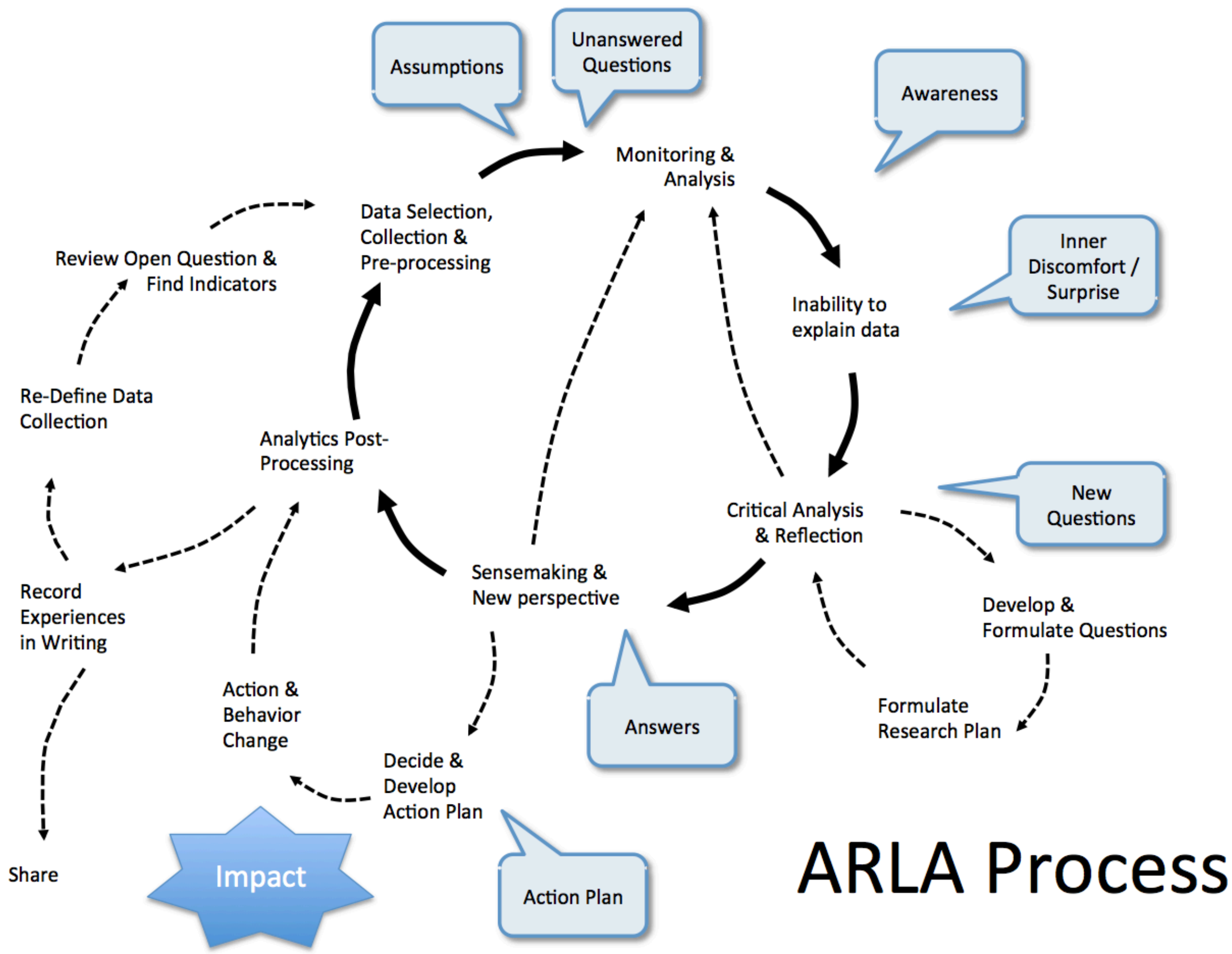

Figure 14. The ARLA process model.

The three phases '*critical analysis and reflection*', '*sense making and new perspective*', and '*analytics post-processing*' are refined by additional process iterations, which can occur during those phases. The models have been integrated in the following way. Basically, the step 'analytics and action' and 'information processing' of Chatti et al.'s (2012a), Elias's (2011), and Clow's (2012) cycles (see section 4.4.3) have been replaced and are described in more detail by extracting the basic principles of AR as well as the four stages of Verbert et al.'s (2013) model. However, Verbert et al.'s (2013) stages 'data' and 'impact' were modified. 'Data' was replaced by 'monitoring & analysis' and switched its location with 'awareness'. On the one hand, the bubbles now represent the way in which the process stages affect a user's mindset. On the other hand, the process stages show the more visible (measurable) activities. This is the reason for switching also the locations of 'impact' and 'behavior change'. A behavior change relates to 'action' in the AR process. Additionally, the ARLA model adds another stage, namely the stage 'inability to explain data'. This is triggered by an experience of surprise and accompanied by a feeling of inner discomfort. This additional stage is based on the definition of reflection, which has been presented in chapter 2. It refines Verbert et al.'s (2013) stage of '(self-)reflection' (see Figure 5, p. 51).

Furthermore, the ARLA model enhances the flow of the process because the iterations of the LA cycle can vary. Experienced users might use the data to become aware and directly make sense of certain aspects of teaching and learning, due to their prior experience (core process). But LA beginners might be unable to explain outcomes of the data collection and pre-processing step. This can stimulate them to form questions and try to answer them. The stage of 'sense making' can motivate an action or even 'change behavior'. The model of Chatti et al. (2012a) again inspired the last step. It is called 'analytics post-processing' instead of 'data post-processing', in order to clarify that the outcome of whole analytics experience is introduced into the design of next iteration of the LA loop. This includes recording the experience in writing, e.g., in order to share it, and revising the data collection and indicator analytics for the next run of the cycle, based on open 'questions' and 'assumptions'.

The iterative flow of the process cycle can be read as follows: Starting from data collection and data monitoring, experienced users might become aware and directly make sense of certain aspects of teaching and learning, due to their prior experience. But LA beginners are sometimes unable to explain outcomes of the data collection and pre-processing step. This stimulates them to form questions and try to answer them. Being surprised, asking, and answering questions stands for reflection as defined by Atkins and Murphy (1993). The stage of 'sense making' can motivate 'action' or even 'behavior change'. This is the impact LA projects strive for.

Questions become only known as soon as real users are using LA tools. Their questions must therefore be anticipated. Which questions could be asked? We need to know this, in order to prepare indicator implementations. Another possibility is to design the system as open and flexible as possible. We could imagine ways, how users create their own questions and indicators, by choosing from different data pools, selecting methods, and deciding about visualizations themselves. However, the later version challenges system designers strongly to make the system user-friendly and to meet privacy requirements.

The ARLA process model was verified and refined through an impact evaluation (see chapter 7). Giving lecturers of university courses access to an actual LA tool gave insights into the influencing factors of the ARLA process (see section 7.5). It answered the questions: Which aspects influence the process how?

5.2.3 Considerations and Constraints

As stated above, each dimension has several constraints that need to be considered. Regarding the 'Who?' dimensions, these are, e.g., competencies of the

LA users, their diversity, expectations, acceptance, data privacy regulations, etc. It is not possible to give a full list of all constraints and limitations here, since each project has unique features and is, hence, influenced by individual constraints. The models of Chatti et al. (2012a) and Greller and Drachsler (2012) give a good overview of possible constraints (see Figure 8 and Figure 9). Therefore, the following paragraphs focus on influencing factors that have been proven to be important in the context of this work's experience, as well as on privacy aspects, which need to be considered by all projects.

Influencing Factors

Diverse factors influence the quality of actual instances of ARLA processes and therefore these factors affect the impact, which LA tools have on users. Chapter 7 presents an impact evaluation. This particular study helped to collect eight factors, which influence the way LA is perceived and the way LA tools are used[4]:

- *Experience, knowledge, and assumptions*: It needs to be acknowledged that each user has certain teaching and LA experiences, which result into diverse assumptions about the learning processes of students. These assumptions are used to explain the data, which is shown by LA interfaces. When interpreting the data, users draw conclusions based on their previous knowledge. This determines their success in finding reasons. Hence, the potential to find something surprising in the data, which needs to be analyzed more closely, is higher, if someone has less experience or wrong assumptions. So, LA has more impact on LA newcomers because there are more opportunities to get them involved.
- *Satisfaction with course*: Teachers have opinions on how well their own courses are designed and how good they are for helping students to learn. These opinions are mainly based on previous experiences with students, former evaluations, and received feedback on a course. So, using LA or other evaluation methods to improve courses might lead to satisfaction with a course design. This state of satisfaction can lead eventually to less involvement in LA and lower usage regarding this particular course. Dissatisfaction, in contrast, can induce higher involvement and interest in LA.
- *Way of using the tool*: An LA tool can be used in different ways. E.g., teachers can monitor the data on a weekly or monthly basis, or they can use the tool only at the end of a term. They can use it systematically with questions in mind and by combining the usage with other data collection methods, or they can use it ad hoc. The way LA is used during the LA activity influences its type of impact (e.g., awareness, reflection, question/analysis, action plan, action) on current or future course designs.
- *Level of surprise*: After detecting something in the data that cannot be explained immediately, the reaction will probably be a 'surprise' or at least 'uncomfortable feelings'. The level of surprise determines the involvement

[4] Note that this list of influencing factors is not exhaustive.

in reflective activities and next steps, but it is also influenced in a decreasing way by the level of 'trust in the tool'.

- *Involvement, interest, curiosity, and lack of interest*: The level of involvement and curiosity regarding the information presented by LA is also crucial for how teachers make use of it. Someone, who is interested in LA and sees a potential in it, will spend more time with it than someone, who doubts its usefulness or who is bored because it does not reveal new meaningful information. A user's involvement can be increased by the detection of meaningful data and surprising situations. But it might drop, if only irrelevant data is presented. How meaningful and relevant the data is, depends on the dimensions of the ARLA model, e.g. user and context.
- *Tool reliability*: It is clear that LA tools need to present reliable results in adequate manner and in appropriate time. If there are problems related to usability and usefulness, this will have impact on the ways users use and trust the tool.
- *Trust in LA tool*: This is about the feeling of a person towards a certain tool. A tool can be perfectly designed and reliable, but if a user does not trust the outcomes of it, he or she will not use it in the intended way. When using it anyhow, the user might blame unexpected data on tool malfunctions. So, regardless of the tool, the analytics will have less impact on improvement activities, unless trust is restored.
- *Support, qualification*: The way a user received and has access to support and qualification for using an LA tool determines the way of how he or she will make use of the opportunities it provides. Supporting features can be integrated within a tool by proving help texts or tutorials. However, other support and qualification activities, such as trainings and a support center will increase impact of LA on AR.

All these factors are determined by an interplay of the dimensions of the ARLA model, represented by the questions: who, why, when, where, what, and how? This is why it is important for LA practitioners and developers to classify their own projects. The factors can also be used for describing target users (personas). Section 7.2 gives concrete use case examples of how the factors can be used and how they influence each run of the ARLA process model.

Data privacy and Ethics

Massive data collection and data storage should sensitize all designers of analytics systems to direct their attention on the possible effects and (positive and negative) impact of their developments. Regarding LA, we need to be concerned with providing a holistic view, but avoid 'big brother' observations of students, and we need to have clear guidelines for dealing with data privacy and ethics.

Although analytics can be based on large amounts of data from different sources, they are unlikely to show all the factors influencing learning. Users of LA tools should know that outcomes of analytical processes are just indicators, which are abstract models (see section 4.4.4) of certain aspects, but not necessarily proof.

On the one hand, it is advisable to ask the right questions and use several of the most relevant data sources for creating better indicators. Then – as research proceeds – we might be able to predict on students' behaviors and outcomes of learning. On the other hand, what might be welcomed by LA users, in order to create a holistic view, might be threatening for the observed individuals, who are tracked (teachers or students). "*Is it good to tell a first-grader, 'You might be a dropout?*" asked MindShift's article 'What are the risks in using data to predict student outcome' (Paul 2013). The author concludes: "*No, we shouldn't tell first-graders—or older students, or employees—that they might be failures one day. But we also shouldn't wait to help them avoid that fate.*" This demonstrates LA concerns, but also responsibilities.

These concerns regarding privacy and 'big brother' were also mentioned by Duval and Verbert (2012). Furthermore, they have been formulated as questions by J. P. Campbell, DeBlois, and Oblinger (2007), such as:

> "*Who determines which data is collected? What obligation does the institution have to inform faculty and/or students that their behavior within an application is being tracked? Does an individual need to provide formal consent before data can be collected and/or analyzed? Does an individual have an option to "opt out" of an analytics project?*" (p. 52)

In an interview on the applications and challenges of educational data, George Siemens remarked:

> "*[…] analytics can't capture the softer elements of learning, such as the motivating encouragement from a teacher and the value of informal social interactions. In any assessment system, whether standardized testing or learning analytics, there is a real danger that the target becomes the object of learning, rather than the assessment of learning.*" (Watters 2011).

Furthermore, "*[…] opportunities exist to use analytics to evaluate and critique the performance of teachers*" (Watters 2011). Duval and Verbert (2012) as well point out the "*danger that 'you become what you measure'*". This would be enslaving rather than empowering and users could, e.g., start gaming the system[5], which certainly is not the intended outcome of the implementation of LA.

In his presentation on 'Practical Privacy Issues Around Learning Analytics' in SoLAR's open online course 2013, Pardo (2013) emphasized the ease of collecting large amounts of personal information. As an extreme example, he pointed out that there are even TVs watching its users. Obviously, all users of such technology should have the right to find out answers to questions like: Who sees the data when and for what purpose? What is collected? What is revealed?

[5] If students are 'gaming the system', this is often understood as 'manipulating the analysis results by superficially changing their behavior'.

Transparency is the key issue behind these questions. For enabling users to see how their data is being used, as claimed by Ferguson (2013), we need clear and accessible descriptions of how data is collected, manipulated, stored and accessed. In the case of LA this calls for answers to the questions: How is data collected? Who has access to the data? Which calculations are performed? How long is the data valid and available? Furthermore, each user should own his or her data and have the right to opt out, to request data removal, or modification. But what effects does this have on analytics outcomes? Only practical experiences can answer this question.

At the first International Conference on LAK in 2011 participants also agreed that LA raises privacy and ethical issues (Brown 2011). In an interview George Siemens stated that "*discussions about data ownership and privacy lag well behind what is happening in learning analytics*" and he posed similar questions as listed above: "*Who owns learner-produced data? Who owns the analysis of that data? Who gets to see the results of analysis? How much should learners know about the data being collected and analyzed?*" (Watters 2011).

In many countries, data is protected by federal, state, and institutional privacy regulations. The 'Directive 95/46/EC of the European Parliament and of the Council of 24 October 1995 on the protection of individuals with regard to the processing of personal data and on the free movement of such data' applies for European countries.[6] Its principles with regard to personal data processing are transparency, legitimate purpose, and proportionality. In other words, this means that the data subject needs to be informed, there needs to be a specific purpose, and the processing needs to be adequate in relation to the purpose.

For example, in Germany there is the Federal Data Protection Act (Bundesdatenschutzgesetz (BDSG)[7] – as of September 2009). Developers of LA tools have to stick to these laws and also should remember that there are people behind the collected data, whose life can be affected in good and bad ways by the interpretations, which will be made (Boyd 2010).

German universities, who are interested in the use of educational data for analytics, have to discuss the data collection and processing with their data protection officers and get approval, who are in turn bound to German data protection legislation. Data protection officials regulate compliance with data protection. Universities in Germany are subject to the national data protection laws. These particularly instruct 'Data reduction and data economy', i.e., using as little personal data as possible. Personal data should only be collected, if it is required for a specific task (BDSG, §3a). However, §4 (1) approves the collection, processing, and use of personal data, if privacy laws either permit it, or if the person concerned has provided consent. Furthermore, it states in § 40 (2) that

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[6] See ‚Protection of personal data': http://ec.europa.eu/justice/data-protection/.

[7] Download the Federal Data Protection Act (BDSG) in English here: http://www.bfdi.bund.de/EN/DataProtectionActs/Artikel/BDSG_idFv01092009.pdf.

processing of personal data for scientific purposes should be conducted in an anonymous form as soon as the research allows.

Boyd (2010) urges to think about the consequences of using personal data and puts into mind that not all data that can be accessed was meant to be used for all kinds of purposes. But she also points out problems with the approach of providing an opt out option:

> "*The accuracy of LA's recommendations for intervention improves as (1) the number of observable "subjects" increases and (2) the amount of data available for analysis is maximized. Analysis based on only a subset of the students in a course or based on fragmentary data will be incomplete. That could mean that the resulting recommendations for intervention might be less accurate. As a result, an opt-out alternative for students could compromise the learning analytics effort.*" (Brown 2011)

Data protection and ethics considerations are very important for the development of LA applications. But they are often in conflict with other requirements. The solution of providing an opt-in and opt-out function, e.g., might lead to useless analytics results in some contexts. Considerations of privacy in analytics are a challenge, which will influence their increasing or decreasing success in future learning scenarios immensely.

5.3 Conclusion

The ARLA reference model demonstrates the five dimensions 'target', 'context', 'objectives', 'environment and data', and 'methods', which all need to be described to get a full picture of an LA project. Based on our previous LA reference model, certain AR aspects were added, which have been identified important in the context of this work. These added elements are the new dimension 'context', the objectives 'monitoring and awareness', 'analysis and reflection', and 'action and behavior change', as well as the ARLA process model.

The ARLA reference model can be used to analyze own projects or related work. By comparing related work in relation to the five dimensions, it is possible to find similar projects and learn from their experiences. The predecessor LA reference model by Chatti et al. (2012a) has been used to give a review of the different dimensions of state-of-the-art on LA and EDM. This fostered an "*understanding of key concepts in this emerging field*" (p. 1). As another example, Greller and Drachsler's (2012) model was used for a survey that aimed at extracting expectations and confidence of stakeholders in LA (Drachsler and Greller 2012). The ARLA reference model makes AR elements more visible. It will help to analyze LA development in this direction. Furthermore, it will help in analyzing general requirements for ARLA projects, such as suggested by the privacy considerations and concerns presented in section 5.2.3.

6 ELAT DESIGN PROCESS

In order to solve the problem stated in chapter 1, design-based methods were chosen to create an LA tool, because there was no adequate artifact available for the intended research, when starting the project. The actual iterative implementation of eLAT served the process of answering the research questions.

Several related works have been developed, and they matured since the early prototyping stages of eLAT (see chapter 2). Also, international as well as local LA research communities have emerged (SoLAR 2013a; GI 2013). This evolution and growing interest in LA shows the relevance of the underlying problem. Findings of related projects were constantly monitored, compared, and their findings were considered within eLAT's and ARLA's design processes.

The user-centered design process was divided in several design stages (mainly in the form of diploma, master, or bachelor works, see: (Bültmann 2011; Hackelöer 2011; Linden 2013; Lisson 2011; Lukarov 2013; Wagner 2013; Zielke 2011)). The results were diverse explorations of prototypes, which were evaluated in each case with respect to several requirements, which were specific for the respective development stage. Parallel conducted literature research also informed the design process, where appropriate. Each prototype revealed new or confirmed previously found requirements for the design of the LA tool. This procedure helped to gain knowledge about LA applications and contexts and proved to be a suitable approach for answering the research questions.

The following chapter describes the design process. Because of the nature of the 'build-and-evaluate' design process, results of evaluations could not clearly be separated in a different chapter. Therefore, the chapter at hand is a summary of main design and evaluation results concerning eLAT. It presents the initial requirements (section 6.1), main development strands (section 6.2) as well as the most important methods used (section 6.3) as well as results of the development and evaluation phases in an outcome-oriented way (section 6.4 and 6.5). Section 6.6 is the last section, and it concludes this chapter with a summary and review of the overall design process.

6.1 General Requirements

Before the design process was started, general non functional system requirements were collected through literature analysis (A. L. Dyckhoff 2011), as well as by informally talking to teachers, e-learning experts and L²P system developers at RWTH Aachen. This early analysis concluded the following main requirements, which could be confirmed by our prototypes and evaluation runs, whose results are described in the following sections (A. L. Dyckhoff et al. 2012):

- *Usability*: prepare an understandable user interface (UI), appropriate methods for data visualization, and guide the user through the analytics process.
- *Usefulness*: provide relevant, meaningful indicators that help teachers in gaining insight in the learning behavior of their students and support them in reflecting on their teaching.
- *Interoperability*: ensure compatibility for any kind of VLE by allowing for exchange and usage of information of different data sources.
- *Extensibility*: allow for incremental extension of analytics functionality after the system has been deployed without rewriting code.
- *Reusability*: target for a building-block approach to make sure that re-using simpler ones can implement more complex functions.
- *Real-time operation*: make sure that the toolkit can return answers within microseconds to allow for an exploratory user experience.
- *Data Privacy*: preserve confidential user information and protect the identities of the users at all times.

This list of requirements was refined step-by-step through iterations of prototyping and evaluations; e.g., with the help of interviews and user tests.

6.2 Development Strands

eLAT was iteratively developed within several development cycles that partially overlapped to meet the requirements. In addition to the development of eLAT, further related studies helped to gain experience with specific demands, such as developing an alternative solution to support data privacy (Hackelöer 2011), the generation of recommendations (Lisson 2011), and the mobile-based collection and analysis of student data (Wagner 2013). Findings of these studies also influenced the final catalogue of ARLA requirements.[8]

The overall eLAT development cycle can be divided into two main lines of action focusing on frontend and backend requirement:

[8] Several paragraphs of the following sections have also been published in (A. L. Dyckhoff et al. 2012). They were included in a revised form with perspective of the current state of the work.

1. Design and evaluation of different versions of user interfaces (UI), and
2. Implementation, testing, and refinement of an overall system architecture.

The design and evaluation of the UI (in strand 1) started parallel to the development of the architecture. An implementation was needed, because there was the need to quickly evaluate high fidelity prototypes with data from real courses. From a software engineering perspective, when creating a new system, it is usually more advisable to first create and evaluate several low and high fidelity prototypes within several smaller iterations for collecting important user requirements, and then to specify the system architecture. But in the case of eLAT, the development of the tool was supposed to build upon existing IT-infrastructures, since LA tools are dependent upon the data from diverse e-learning environments. Meaningful evaluation results with user testing can only be achieved with prototypes that incorporated the individual teaching and learning context of a particular user. It was possible to evaluate general usability issues without real data, but it was impossible to figure out, if the tool was really meaningful to a user.

Hence, both lines of action (strand 1 and 2) were conducted parallel and informed each other, were appropriate. This development decision led to the advantage that we could start to conduct pilot evaluations with real users and courses earlier. But there was also a disadvantage: Some design decisions concerning the system architecture (e.g. database design) that had been made based on early UI prototypes had to be revised later because of lessons learned with the help of more mature high fidelity prototypes and grounding these in theory. However, the drawback of creating high-fidelity 'throw-away' prototypes was accepted for the benefit of being able to conduct meaningful evaluations in the context of actual university courses. It was not a disadvantage, but rather an important lesson learned. These experiences with imperfect system versions were valuable for learning about how not to design a system that aims at achieving reflection and AR. It also helped to check the accuracy and completeness of the list of non functional requirements (see section 6.1), e.g., based on our findings, we decided to include the requirement 'correctness' in the final requirements catalogue for ARLA tools (see section 8.1.1).

The UI engineering process was iteratively conducted, whereat each of the main iterations build upon former results and had specific objectives (Bültmann 2011; Lukarov 2013; Linden 2013). Each of these main iterations comprised several smaller design, prototyping, and evaluation iterations themselves; e.g., especially the works of Bültmann (2011) and Linden (2013) included the evaluation of several paper prototypes before implementing operational UIs. In strand 2, eLAT was designed as a prototype to evaluate a software architecture for LA using two VLE platforms (Zielke 2011). The objective was the creation of an LA framework, which was intended to comply with the non-functional requirements (see section 6.1).

6.3 Methodology Toolbox

Besides literature reviews the most important methods used during the design and evaluation process have been:

- *Prototyping*: This is a type of formative evaluation of design concepts in early stages of the development of interactive systems. For prototyping, it is essential to have a good design-concept at the start and improve it iteratively. Approaches to prototyping are 'through-away', 'incremental', and 'evolutionary' (Dix et al. 2004).
- *Semi-structured interviews*: Semi-structured interviews are a high-level evaluation technique to collect facts, talks, opinion and attitudes of the interview partners by asking a set of questions. The interviews are guided through prepared questions, but they are also flexible because it is also possible to ask questions spontaneously to investigate interesting details (Dix et al. 2004). Interviews are well suited for exploratory studies (Nielsen 1993).
- *Questionnaires*: Creating a questionnaire is a helpful method for analyzing users' goals and tasks. It is a similar method to interviews. Users can fill in the answers by themselves, but questionnaires are not as flexible. However, they may also contain open-ended questions, so users can reply in natural language.
- *Heuristic evaluations*: A heuristic evaluation is a usability inspection method. It uses approved rules of thumbs, usability principles, or guidelines to investigate the usability of a UI. The guidelines used in this method can be general or product-specific. An example for a general guideline could be "provide feedback". Heuristic evaluation with, e.g., Nielsen's 10 heuristics, Shneiderman's eight golden rules, or Norman's seven principles (Dix et al. 2004), can help to discover usability problems with little effort in early development stages (Nielsen 1993).
- *Cognitive walkthroughs*: A cognitive walkthrough is also an inspection method for early development iterations, but it needs more preparation than heuristic evaluations. E.g., it needs a specification of the users, the UI, and descriptions of tasks as well as lists of actions to evaluate the usability. With the help of the tasks the UI can be processed step by step to discover usability problems and focus on the ease of learning the system (Wharton et al. 1994; Dix et al. 2004).
- *Pluralistic walkthroughs*: The pluralistic walkthrough is similar to the cognitive walkthrough. It is a meeting of subject matter experts of different domains, such as users, designers, and usability specialist. They discuss elements of the interface prototype according to the view of the users. Basically, they perform a heuristic evaluation (Nielsen 1993).
- *Think aloud*: In this formative evaluation method users are asked to perform tasks with a software prototype, whereat they are talking about what they are doing and thinking. This way, misconceptions can be

detected more easily. During the tasks the evaluator observed them (Dix et al. 2004).

Usability inspection methods, such as 'cognitive walkthroughs' or 'heuristic evaluations', should not replace empirical testing with users because the latter delivers the richest information. But they can be quite effective in early stages of the development cycle because they are efficient, less expensive, and also might suggest potential fixes to problems (Desurvire 1994, p. 195f). According to Desurvire (1994), empirical testing with users should be performed rather near the end of a development cycle to discover unpredictable problems. Nielsen (1993) suggests combining various usability methods and specifically he recommends: "*A combination that is often useful is that of heuristic evaluations and thinking aloud or other forms of user testing*" (p. 225). This way, distinct sets of usability problems can be found.

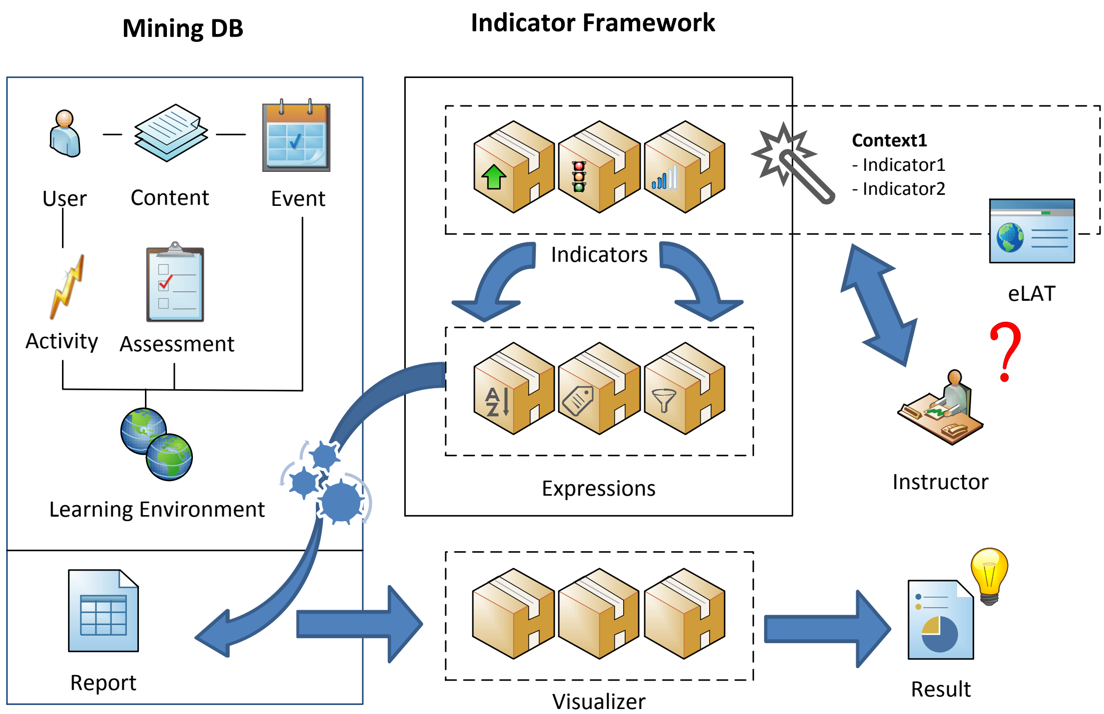

Figure 15. eLAT's system architecture. Source, Zielke (2011).

6.4 Framework Design

eLAT's architecture, the main result of development strand 2, is presented in Figure 15. The requirements 'interoperability', 'extensibility' and 'reusability' (see section 6.1) demanded a flexible coupling of VLE infrastructure, which was modeled on the model-view-controller (MVC) pattern, whereby the implementation of an indicator evaluation process represents a controller and the visualization system generates the view[9].

eLAT encompasses three main components, namely an indicator framework, a mining database, and a visualizer application. The indicator framework negotiates and provides report evaluation services, i.e., executions of indicator calculations, between the website and the mining database, while the visualizer component provides an abstraction layer for visualizing different reports.

6.4.1 Indicator Framework

The indicator evaluation process is illustrated in the numbered (green) boxes in Figure 16. A teacher visits the LA tool and accesses an indicator (step 1). The indicator framework dynamically instantiates a controller for this indicator. This will create a view, containing user interfaces for all the available configuration properties (step 2). After the user has finished adjusting all the properties the configuration is validated. The framework will generate a report evaluation request, store it in the report database, and send an evaluation request to the evaluation service instances. In the meantime the user will be redirected to a waiting page that displays the current evaluation status and updates automatically (step 3 and 4). Once the evaluation has completed the report, consisting of the initial configuration and a dataset of raw data tables, it will be stored permanently in the report database (step 5). Storing the report results can help to improve performance, if the same report is supposed to be loaded more than once. While querying the report status the client side scripts will eventually learn of the successful evaluation and load the dedicated JavaScripts that will then generate and show the appropriate visualization based on the raw data set obtained by the report service (step 6 and 7).

The system architecture of eLAT was designed for extensibility and reusability of the existing code base, so that the scope of operations can grow. Therefore, a single indicator implementation makes use of smaller parts in the form of expressions that are performance-optimized database queries to retrieve specific result sets that can be useful for other indicators as well (see Figure 15). The same practice is applied to the dynamic user interface generation for indicator parameters and the visualizers, which operate on standardized datasets and are therefore generic to the data inside the report. This is supposed to reduce the effort for implementing new indicators.

Most of the server-side code is written in .NET and uses Windows Communication Foundation (WCF) services for providing data and communication interfaces between the website, the evaluation service and the client site visualizations. The indicator website itself does not generate much load on the CPU or the database, but the evaluation processes are computationally intensive and, hence, time-consuming. Therefore, for each evaluation, these

[9] Former version of the following paragraphs have been published in (A. L. Dyckhoff et al. 2012).

processes should be executed by dedicated services. These have to be run in multiple instances, ideally on a different physical machine, to approach real-time operation requirements.

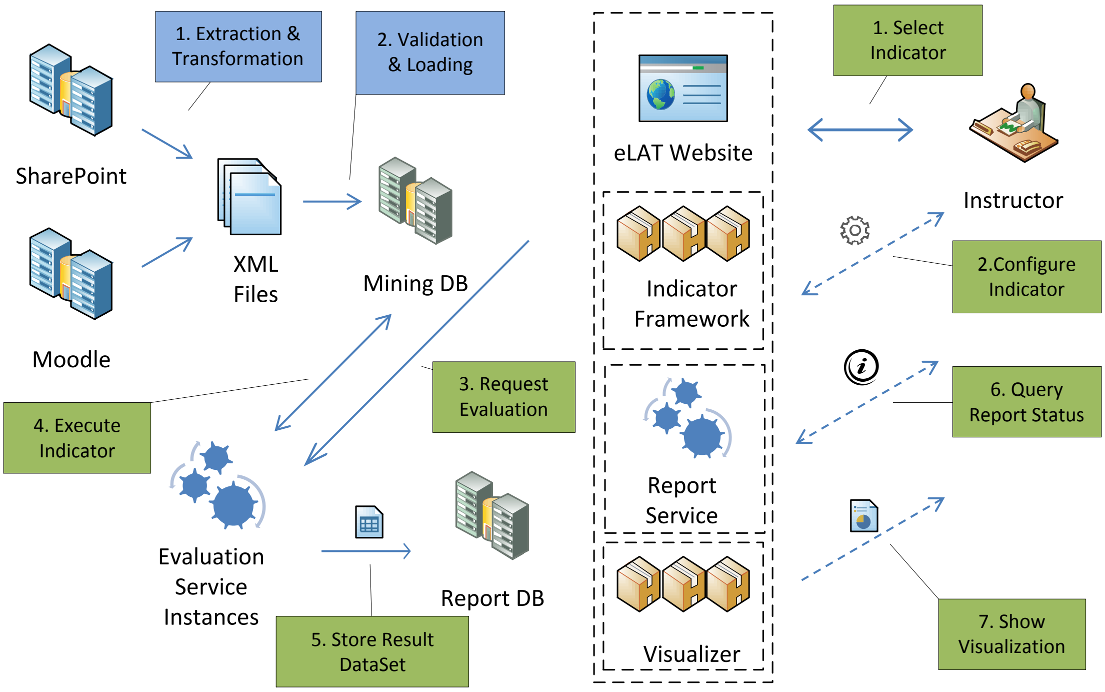

Figure 16. Indicator evaluation process. Source, Zielke (2011).

To allow for upgrading and enhancing of analysis methodology while the system is deployed, the implementation makes use of the Managed Extensibility Framework, which allows for dynamic composition and object instantiation of software capabilities.

6.4.2 Data Model

Since the eLAT implementation is supposed to be independent from a particular VLE, we searched for a neutral (standardized) data model that supports all the major data types as well as an extension model to fit in special types. At the time of creating this data model, there was no established data format, which could be adopted. The orientation of data types, such as assessments and resources, towards a specific VLE, runs the risk to become dependent on this system. These systems are not designed for data collection and analysis. They are not designed for data mining. Hence, "*its thorough analysis requires long and tedious preprocessing*" (Krüger, Merceron, and Wolf 2010, p. 131)

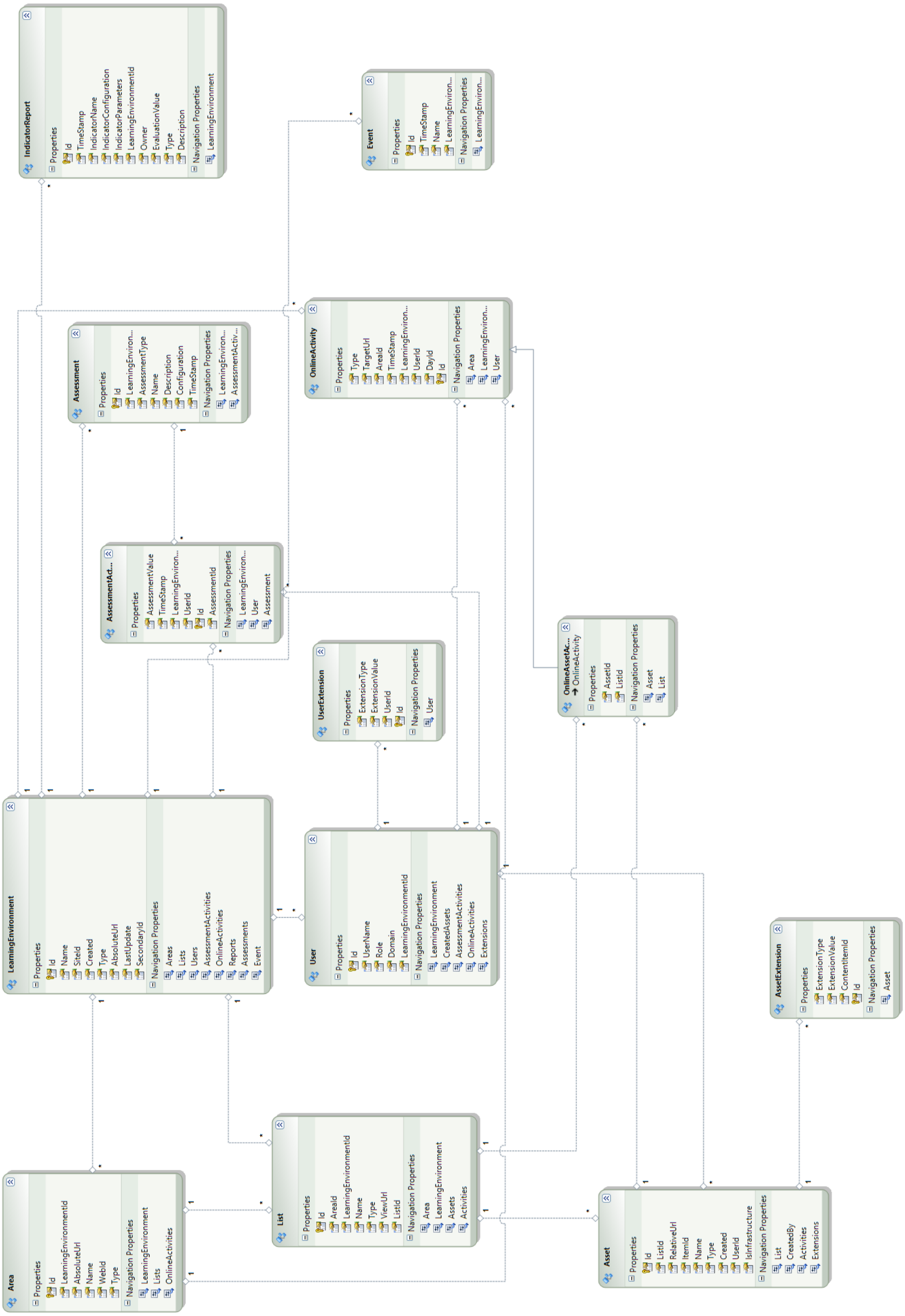

Figure 17. eLAT's data model.

For data mining, Krüger, Merceron, and Wolf (2010) present a data model to structure and export usage data, which comes from learning environments. Still, from this work's point of view, they oriented the design of their data model to the LMS Moodle, which in turn is similar to SCORM. Hence, they took a lot of dependencies from the database structure of Moodle. Their data model did not allow for integration of more detailed information or extensions. Under these circumstances, the storage of personal data, such as gender, age or specific prior knowledge could not be implemented (Zielke 2011).

In the case of the first version of eLAT's data model (Figure 17), we modeled a learning environment as a general virtual learning space dedicated to a specific course, which could be implemented in any VLE. Hence, the central element of the data model is the object 'Learning Environment'. The 'Learning Environment' can include several objects of the types 'User', 'Activity', 'Event', 'Assessment', and 'Area', which are connected to lists of assets (resources)[10].

Each user object corresponds to exactly one user identity (one person). But a user (one person) might have multiple identities, if she is taking several courses. The user object is assigned a pseudonymous user identifier to protect personal data. It also stores the role of the user, e.g., 'instructor', 'tutor' or 'student' and it can hold custom properties in 'User Extension', like gender, field of study, or additional information, which can be added to enhance the model for new analytics purposes. Sometimes users can have multiple roles within one course. For example, in L²P a teacher can additional book himself as a student in his virtual course room in order to have a student's preview of what students can see. In this case, the role with highest privileges is used. This ensures that the activities of instructors are not mistakenly counted as a student's activities (Zielke 2011).

Also of central importance is the linkages of 'User' objects to 'Activity' objects and content, represented as 'Asset' in the data model. Thus, each activity – along with timestamp and user information – is clearly assigned to an actor and each object is assigned an owner (see 'CreatedBy' field in Figure 17). 'Asset Activity' logs interactions with content. The interaction types can distinguish between create, view, change, delete, copy, rename, and search for individual assets.

An 'Event' is a scheduled temporal unit, which is important for a blended learning design. As typically every course has a calendar and special events like course start, assessment and exam dates, it is useful to use this information in the parameter selection and analytics visualization process. E.g., it is a requirement to narrow down the activity to certain time spans such as the time between two exams or visualizing the usage statistics of the forum activities only in the time between two evaluations of weekly assignments, which then could be defined as events. An event is not necissarily part of a VLE. One example for an event is a traditional face-to-face lecture. The event object was introduced in the data model

[10] This and the following paragraphs are a partly cited from A. L. Dyckhoff et al. (2012) and enhanced by giving more detail about the data model based on statements of Zielke (2011).

to integrate lectures, field trips or examination dates in the analysis. But it could also be used to store other activities that should be highlighted; e.g, the event of sending an important reminder notification to all students. It can be interesting to use events as variable parameters for configuration of investigations to correlate them with other data and check for dependencies.

For some activities, like exams, it is essential to store the outcomes. The interactions of users with assessement assets are held in activity objects. Hence, an ‘Assessment Activity’ only needs to save the value of the assessment outcome. Additionally, we wanted to store assessment instances separately from the user submission to allow for different handling and support of various assessment types. This also supports an extension model to fit in properties like completion time or group work submissions, which are not common, but sometimes available.

In most VLE, there are multiple sources of content data, structured by using content areas and content lists or libraries. Therefore, the data model includes the objects ‘Area’ and ‘List’. Collaborative, interactive features or content are frequently arranged in separate areas, such as a learning materials section or group workspace areas, in order to facilitate navigation. Furthermore, several external systems can be used in a course, such as platforms for the provision of videos or electronic tests in addition to the central VLE. The semantic distinction into areas can be re-used in the analysis. Algorithms can, for example, differentiate the areas for storage of documents or collaborative areas with forums and wiki pages by using the ‘Type’ field.

Table 11. Similarities of eLAT's data model to IMS LD.

eLAT	IMS LD
User	Person
Role	Role
Activity	Activity
AssessmentActivity	Outcome
Learning environment	Environment
Event	Method, support activity, notification
Asset, lists, areas	Learning objects, service

List and libraries can be used to organize elements of the same type or context, such as lists of wiki pages or similar learning resources. The individual elements are referred to as ‘Assets’ in the data model. An asset stores the name and a type of an asset. It also records which user created the element and when it was created or last changed. The field ‘IsInfrastructure’ is used to highlight elements, which are part of the infrastructure of the learning environment. This way, graphics, documents, or web pages can be marked, if they are just needed for the documentation of the design or functions of the LMS, but serve no actual learning objective. Additionally, there are ‘Asset Extensions’ dedicated to extent content items with properties that are not always available, like for example a forum post, which has a property for the depth inside the discussion thread – in any other case that post can be regarded like any other content item, with properties like title, creation date and the user responsible.

The eLAT data model can be compared to the main objects of IMS Learning Design (IMS LD) (see section 5.1.4), which is illustrated in Figure 18 and Table 11 (see also Figure 17).

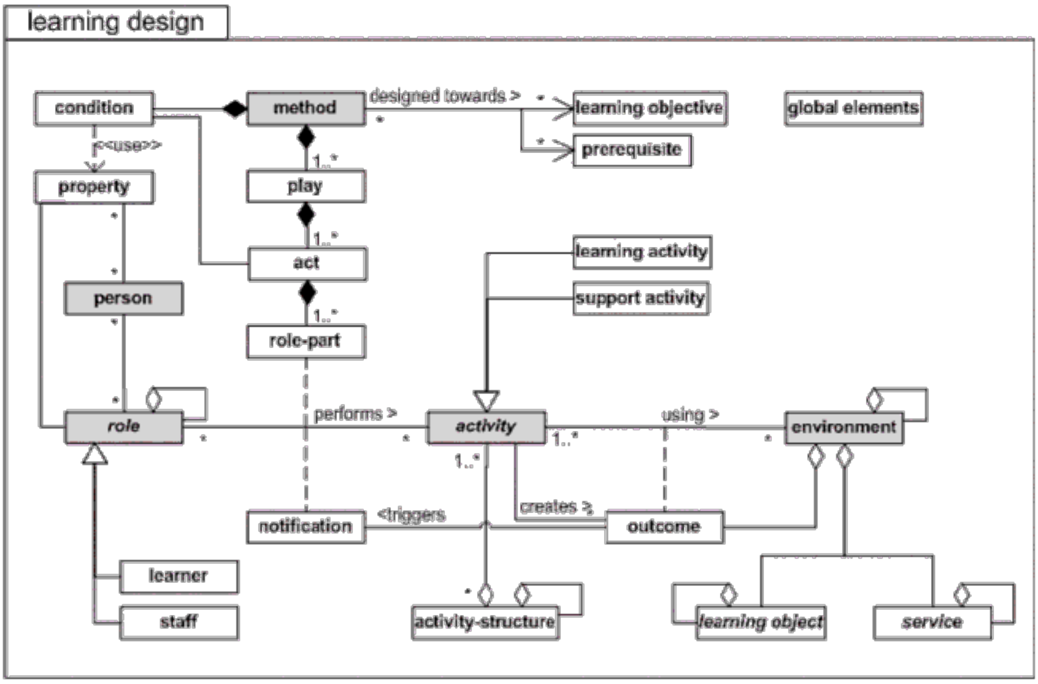

Figure 18. Conceptual model of IMS Learning Design. Source, IMS (2003).[11]

For the prototype evaluations of the framework’s design, data of courses from L^{2}P and a Moodle instance, which was used in one course to host assessments, was extracted (Zielke 2011). In order to extract and transform data to the data model, custom code was used for each VLE, as shown in the blue boxes in Figure 16. Also, a general XML schema, which can be used to create and validate XML files from any VLE data output, was specified. The user interface evolution (see section 6.5), which continued also after the backend was implemented, as well as pilot phase experiences revealed limitations and the need for enhancements of the first design of the data model.

[11] Copyright © 2003 IMS Global Learning Consortium, Inc.

6.4.3 Data Privacy Realization

Data privacy was one of the general requirements for the LA tool (section 6.1). Indeed, it turned out to be a relevant issue, concerning the realization of evaluation phases with real courses and real data, e.g., data privacy regulations affected the selection of pilot courses during the impact evaluation (see chapter 7). We learned that the way data privacy is considered is an important criterion for the successful integration of LA applications in higher education (see section 5.2.3).

E-learning and especially LA are in an area of conflict between the goals of research, teaching, and privacy policies (Hackelöer 2011). Educational systems store sensitive data that impact users' privacy. LA developments need to consider this, when using this data.

To ensure data privacy, the personal data, which can be extracted from a VLE, needs to be modified. We chose to store pseudomized data, in order to be able to uniquely distinguish between the data of different users while securing their identity. For eLAT, a hash from the username with a learning environment specific salt was created, so that the transformation is not easily reversible. The algorithm used was MD5 with a hash size of 128 bits (Rivest 1992). Also the use of any kind of personal user properties like gender or study course in the indicators was prevented, when there were less than a certain number of students, e.g. five users with that certain property in a course, in order to prevent identification of users with unique properties.

During the research for this thesis, also an alternative possibility was explored: a contract-based system that regulates the use of analytics interfaces by so-called 'contracts' (Hackelöer 2011). These contracts form an intermediate instance that checks requests before calculations are performed and outcomes delivered. A contract contains three categories of dynamic conditions: preconditions, postconditions, and invariants. Pre- and postconditions specify conditions, which must be met by the caller of an interface or the callee. Invariants define conditions that must hold before and after the execution of each method of a class, but not necessarily during the execution of a method (Meyer 1992).

Contracts are more flexible than the concept of static typing present in many programming languages, for which already ranges of values for input and output parameters are defined, which can be regarded as a pre-and postconditions. The parameters of the contracts, however, can relate to each other. An example is the precondition:

> *If parameter A is in range of X, parameter B must be in range of Y, or in the range of Z.*

Because of this, the validity of data regarding the contracts can only be checked at runtime (Hackelöer (2011), p. 31).

According to Hackelöer (2011), a contract, which is regulating the use of an analytics interface, is based on up to four dimensions:

- the user inquiring the system,
- the type of data being inquired,
- the courses which are targeted by the inquiry,
- results of the inquiry.

A contract evaluation process begins with the request of a user. This person selects one or a set of courses and chooses an indicator with specific parameters. *For instance, an RWTH computer science teacher selects his current programming lecture and chooces an indicator, which tackles the question "Is wiki page access related to gender?".* The system completes this request by adding information on the required data for the indicator, *e.g., data on access to wiki pages by gender.*

Then a contract audit is carried out: First, all matching contracts that do not relate to the outcome dimension are processed. A matching mechanism determines those contracts that must be fulfilled. *Regarding our example, these are all contracts relating to the three dimensions: RWTH user, wiki pages by gender, and RWTH course.* An analysis process evaluates the request data against the constraints imposed by these contracts. *Such a contract might, e.g., determine that only registered user are allowed to request this information.* If the request can withstand this test, the database query and indicator calculation is released. A transformer regulates the transformation of the data request into the appropriate format for the data access module in both directions. Once the results are available, the contract system checks the pending contracts regarding the outcome dimension. *For example, there might be a contract defining that there has to be at least data of five students of the same gender, if gender data is requested by an indicator.* If the test is positive, the data access module is granted access to the data. Subsequently, the indicator can make the necessary calculations on the data. However, data access will be denied if one of the contract checks during the whole process is negative. *Regarding the example, this would be the case, if there were, e.g., less than five female or male students registered for the programming lecture.*

By means of this contract-based analytics process, it is possible to allow a more open provision of indicators. In other words, advanced analytics users could get permission to define new indicators themselves and analyze the results, provided that the contract evaluations allow it. However, a detailed and careful definition of the contract database together with policy experts constitutes an important prerequisite. Contract-based design should be tackled by future versions of eLAT[12].

[12] For details about the implementation of a contract-based framework see (Hackelöer 2011).

Table 12. Example XML file for importing L²P data into the eLAT database.

```xml
<?xml version=”1.0”?>

<AuditExport
    xmlns:xsi=”http://www.w3. org/2001/XMLSchema−instance”
    xmlns:xsd=”http://www.w3.org/2001/XMLSchema”
    ExportDate=”2010−12−22T16:10:02.4948859+01:00”
    SiteId=”4ad20579−86cb−43dc−a618−f0b3115a8d51 ”>

<AuditItems>
    <AuditEventItem
        EventType=”View”
        EventSourceType=”Document”
        EventSourceUrl=”ws10/10ws−19089/shared/discussions/display.aspx”
        EventSourceId=”e16ccad9−86 cd−4ef7 −8345−8d1c039e9589”
        SiteId=”4ad20579−86cb−43dc−a618−f0b3115a8d51”
        UserId=”ED6BD965008D3428C05E27E6B630D1F9”
        Occured=”2010−12−14 T14:05:52+01:00” />
    <AuditEventItem... />
</AuditItems>

<ContentItems>
    <ContentItem
        xsi:type=”ContentList”
        FriendlyName=”Hyperlinks”
        SourceType=”List”
        SourceUrl=”/ws10/10ws−19089/information/hyperlinks/all.aspx”
        Id=”89d71d89− a112−4acd−9075−1b51686a70d1”
        CreatedBy=”475DCA6D15E6B7723C3A18B89B364779”
        Created=”2010−09−21 T10:31:04+02:00”
        ListType=”Links” />
    <ContentItem…/>
</ContentItems>

<Users>
    <User
        UserName=”044A9414FD72DBF2C5C40F355FBD40C2”
        Role=”Student”
        Domain=”CAMPUS” />
    <User…/>
</Users>
</AuditExport>
```

6.4.4 Data Import

For importing the VLE usage data into the eLAT database, an XML schema was defined. The respective XML file contains three main elements:

- *AuditItems*: These are individual requests of a specific user on a specific content.

- *ContentItems*: These are the resources of the VLE, which can be accessed by the users, and their respective creator.
- *Users*: All users who have either accessed an AuditItem or created a ContentItem.

An example file is shown in Table 12. But this was not the only data that was needed for some indicator calculations. Therefore, other systems need to provide, e.g., personal data or performance data.

6.5 User Interface Evolution

The first main iteration of strand 1 regarding the design and evaluation of a UI – mentioned in section 6.2 – dealt with the collection and definition of indicators (Bültmann 2011). Since the concept aimed at enabling teachers to explore educational data of their students and courses based on graphical indicators, it involved the collection of indicator ideas as well as assigning priorities to them. Thus, semi-structured interviews were conducted with eight teachers (6 male, 2 female) to evaluate a set of graphical indicators (see Figure 19) before actually implementing them, and in order to get to know further indicator ideas and user requirements. Several indicator visualizations were collected from literature or developed by us in brainstorming sessions. Sketches or printed diagrams were shown to and discussed with the participants during interviews to collect facts, opinion and new ideas.

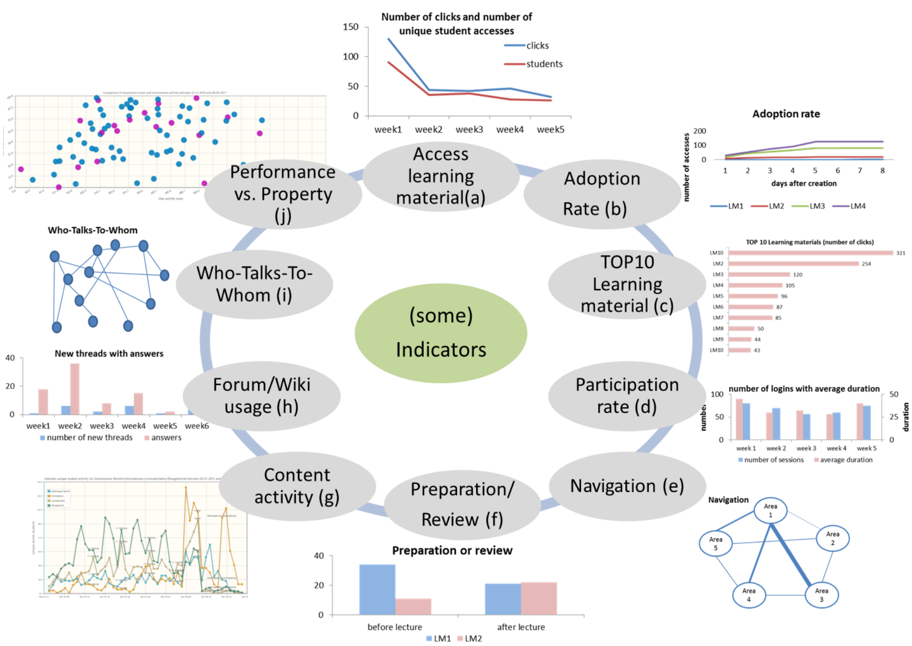

Figure 19. Example Indicators. Source, Bültmann (2011).

We also asked the participants about their personal goals. All participants' analysis goals were oriented towards quality and activity. It was important for seven interview participants to monitor activity, like the frequency of logins or the dates and occurrences of accesses by students. They wanted to monitor, if continuous learning is taking place and if this leads to better learning results (mentioned by all participants). Therefore, it was concluded that it is important to relate the usage and access of learning material with performance. These findings were similar to the results found in a literature study (A. L. Dyckhoff 2011).

Furthermore, indicators concerning activity or achievements were valued most. Seven participants rated the indicator 'number of clicks and number of unique student accesses' (see Figure 19) as helpful for general overview, especially in the beginning of using a VLE. But it remained unclear, if this indicator can always deliver interesting information. It was concluded that such indicators should be used in combination with other data. Six participants stated that 'adoption rate' was interesting to them, because of its visualization of students' timely reaction to file uploads. Teachers could relate it to teaching events, such as making an announcement, and observe changes in student behaviors. The 'top 10 materials' indicator was identified as a valuable measure (7 participants called it 'important' and one 'somehow important'). It was interpreted as helpful for identifying those resources that are somehow relevant for students. A 'top 20' might be better suited for courses with large amounts of resources. By monitoring, e.g., 'activity areas', it seemed to be possible to identify patterns, such as 'at what times students do their exercises', or whether they 'access learning materials before or after lectures'. In general, the usage data indicator were pointed out to be well suited for first impressions during analysis, i.e., for getting a quick overview about what has been going on in the past semester. Regarding assessment data, besides correlations with the activity of students, teachers also wished to take a deeper look at correlations with properties, like the program of study, the duration of study, and the students' native languages. Five out of eight participants stated that such indicators could be important and one thought it was not important. These diversity filters could be important for adjusting teaching methods for specific groups of students. Teachers had divergent opinions on examining active collaboration and communication, e.g., the usage of forums or wiki pages. Four participants rated it as an important measure, because communication, discussion, and participation are represented in collaborative features. The other half gave lower priority to it, because of low participation rates in their courses, and because students were using other collaboration tools outside the teacher-controlled VLE. The assessed usefulness of collaboration and communication indicators therefore heavily depends on the participation of the students in an online course and the relevance a teacher ascribes to it. The reason can be found in the underlying structure of the TEL courses at universities. Communication often takes place outside the VLE, e.g., in face-to-face meetings. Students talk and learn together outside the online learning environment, and thus, communication and its relation to learning cannot be measured adequately, unless specific (mobile) data collection tools tackle this issue (see, e.g., Wagner (2013)).

After collecting ideas about possibly meaningful indicators, which an LA tool could provide, the next question was, how to present the indicators to users in an understandable und usable way. Therefore different UI designs were evaluated within several design iterations.

The second main iteration of strand 2 focused on the design, layout and data presentation of the UI (Bültmann 2011). Design and data presentation of diverse prototypes were informed by dashboard design principles of Few (2006) and evaluated in terms of heuristic evaluation, cognitive walkthrough and pluralistic walkthrough. The first two methods were chosen to evaluate the low fidelity (paper) prototypes of the UI in early stages of development. Later a variant of the pluralistic walkthrough was conducted, where a domain expert, a usability expert, and the designer discussed the interface from different users' perspectives.

The third iteration, which was mainly concerned with interaction, included a qualitative think-aloud study (Bültmann 2011). This method was chosen to identify areas of interactions where users made mistakes. The evaluations of the first and the second iteration were performed with the help of paper prototypes. The third iteration was a functional UI, which was implemented based on previous evaluation results. It was developed in parallel with the backend framework (see section 6.4), and it was used to investigate interactivity and usability aspects.

Besides the usability evaluation methods described above, there was an inevitable need to develop a methodology for impact analysis. As shown by Dyckhoff et al. (2013), impact had not been properly measured in the LA research field so far. Therefore, an impact evaluation method was designed and the impact analysis was conducted on the basis of 'eLAT User Interface B' (Launchpad), which was the result of the third UI iteration (see section 6.5.2). Chapter 7 gives a detailed overview on the results of this impact evaluation.

In the fourth UI iteration all earlier findings, including the impact evaluation findings, were applied to again specify, implement and evaluate several variations of the final interface, named ARLA tool – a high fidelity prototype of the ARLA model, which is an implementation of the ARLA model, and one of the major contributions by this thesis's research (see section 8.2 and chapter 5).

The following sections preserve the evolution of user interface designs. It is meant to give an understanding of the diverse designs, which were evaluated and compared in order to compile all experiences in the final ARLA specification. This way, other LA tools can be compared to the different stages described in the following sections.

6.5.1 eLAT User Interface A (Wizard)

The first interface of eLAT consisted of a series of pages that a user had to interact with before single indicators were displayed (Zielke 2011). This process was similar to a wizad-based system that guides users step-by-step to reach a certain goal. The implementation of this UI was embedded within the development of eLAT's general architecture (section 6.4). It was more of a technical prove-of-concept, rather than a UI, which had the objective to achieve good usability. There were, especially some deficits regarding the goal of minimizing the number of clicks. Nevertheless, it was a first step for collecting data within real world conditions (e.g. data policies) and visualizing it with dynamically generated indicators.

For clarity, indicators were structured by categories (named 'contexts' by (Zielke 2011)). Hence, in the first view of the above described UI a plain list of indicators' categories was generated. The user could select a category, then view the associated indicators, select an indicator, and was then directed to a page that showed him various form fields. These represented the various parameters for one indicator. After selecting the parameters an evaluation request was send to the eLAT backend framework (see section 6.4 and Figure 16), and the results were presented within a web page.

Examples of Indicators

Three indicator examples, which had been implemented and tested in the first UI, are presented in Figure 20 to Figure 22.

The first visualization in Figure 20 shows the percentage of inactive (black), very active (blue) and active students (green) based on am activity definition, which can be defined by users themselves in a previous step. For example, the user could define an 'active student' as somebody, who submits assignments and logs in at least two times during each week. The diagramm is based on real data of an RWTH programming lecture. The week that is showing a higher percentage of inactive students in the center of Figure 20, is related to Christmas break in December.

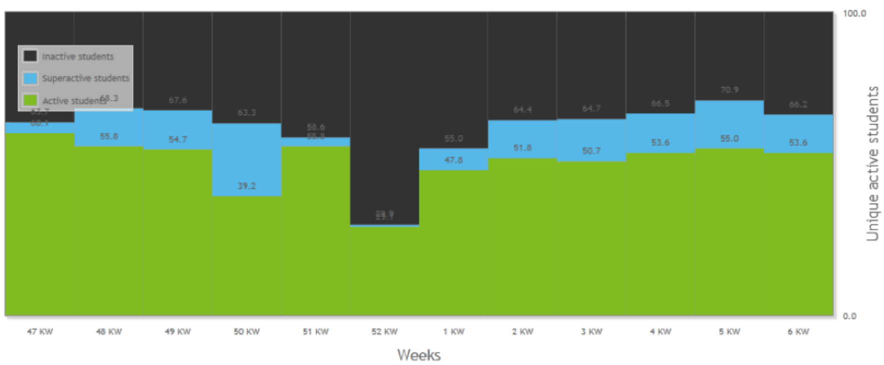

Figure 20. Indicator on 'activity status of students', of eLAT's UI A (Wizard).

The second indicator in Figure 21 is supposed to visualize how fast selected learning materials have been accessed after they have been uploaded to the VLE. It was also generated based on real data.

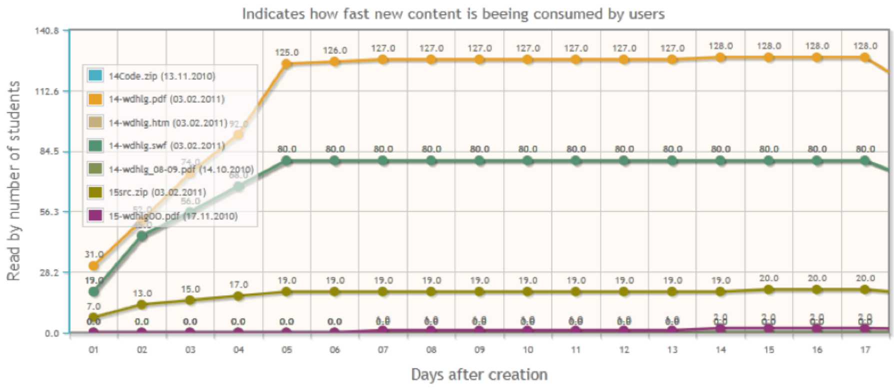

Figure 21. Indicator ‘degree of usage’, of eLAT's UI A (Wizard).

The third visualization in Figure 22 presents a bubble chart that correlates assessment with user activity scores and fields of study. The colors of the dots represent different fields of study. Since randomly generated data had to be used for this visualization, no correlation can be found in this example.

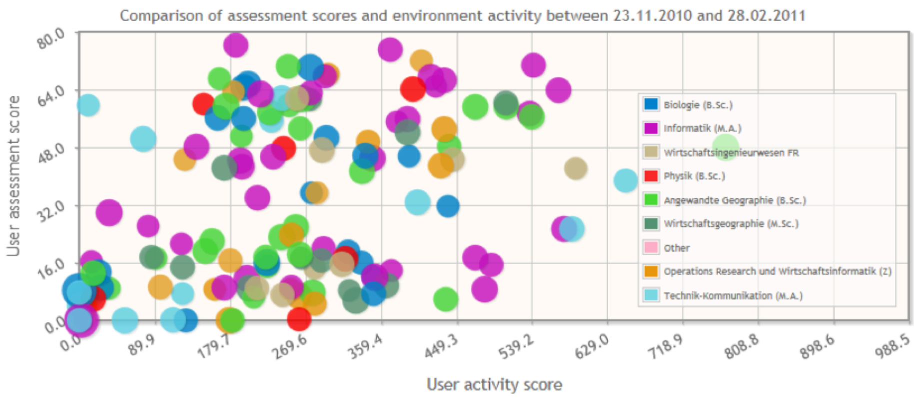

Figure 22. Indicator ‘correlation of assessment data’, of eLAT’s UI A (Wizard).

The advantage of the above described interface was mainly from a technical perspective. Only the intended evaluation requests were sent to the server. This way, redundant evaluation request were avoided, saving computational power for reports that were explicitly requested by users. A user, who knows what she was looking for, basically was able to get this information, but unfortunately only after a few clicks (on categoris, the specific indicator, and its parameters). The interface was less suitable for LA newcomers, since they had to start using categories and indicator parameters without having an idea of the analytics results. However, this interface had not been designed with a focus on good usability, but served mainly as a proof-of-concept for the visualizer component within the main task of developing an entire LA framework (see strand 2).

Therefore, parallel to the framework development, a usability engineering process regarding the eLAT interface was conducted (strand 1). Interviews with potential users and the evaluation of several paper prototypes resulted in eLAT's interface B – a launchpad, which is described in the following section.

6.5.2 eLAT User Interface B (Launchpad)

The structure and layout of eLAT's user interface B was the result of an iterative usability engineering process (A. L. Dyckhoff et al. 2012; Bültmann 2011).[13]

The result of this process was an LA launchpad. The functionalities of a launchpad go beyond the functionalities of a dashboard, since it provides broader opportunities for analysis (Few 2006). Nevertheless, when a user accesses the system for the first time, he sees an initial dashboard-like overview. In eLAT, this view is called 'monitoring view' because it was primarily composed to compile important information in one screen so that the user can monitor it at a glance. Hence, the monitoring view helps to observe several indicators at once (Figure 23). The main idea of the dashboard was, to directly show several indicators to the users. This way, beginners did not have to choose indicators from lists, which they did not understand. Instead, they could immediately have a look at analytics results based on current data.

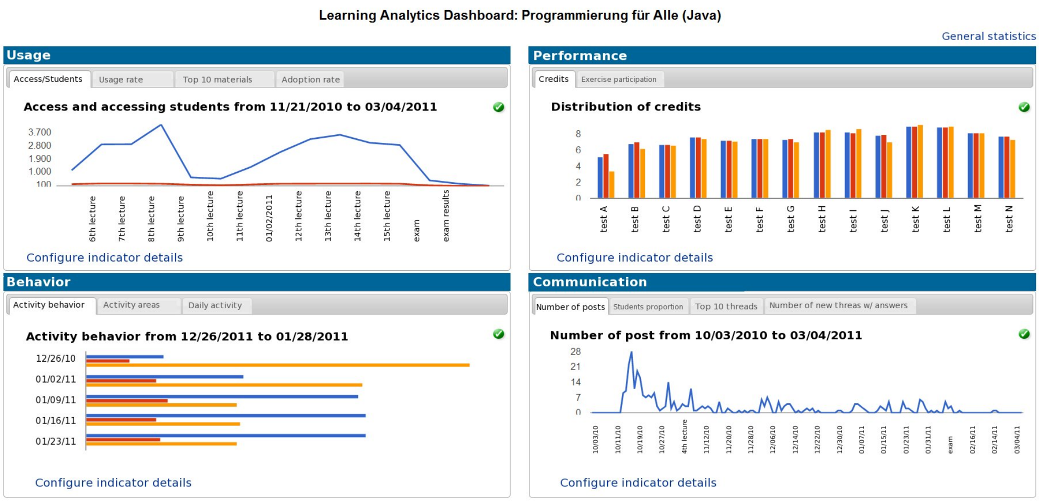

Figure 23. Monitoring view of eLAT's UI B (Launchpad).

The monitoring view was designed according to acknowledged design principles for dashboards (Few 2006). Thereby, the challenge was to clearly present a lot of

[13] The following sections are a revised citation of A. L. Dyckhoff et al. (2012).

data on limited space. Information overload needed to be prevented. As a result of user studies and literature recommendations, the monitoring view was divided equally into four indicator widgets. Since, more than only four indicators were requested by the users, each widget grouped several indicators along a theme. In this sense, the widgets were containers for indicators related to the categories ‘document usage’, ‘assessment/performance’, ‘user activity’, and ‘communication’. These overall categories were determined though literature research and user interviews (Bültmann 2011). Each indicator could be displayed quickly via a click on its respective tab. The idea of using widgets and tabs was supposed to help in terms of personalization, since they can be arranged flexible by users. It was planned to improve personalization by letting users arrange the order of widgets and tabs, or letting them decide, which indicators to delete/add. However, this was not implemented in the high-fidelity prototype, which was used for evaluation.

Based on the indicator visualizations in the dashboard overview, a user could call on an ‘analysis view’ for each indicator. The analysis view provided a deeper insight into the data of a chosen indicator. It provided filtering options and made it possible to drill down into details. Additionally, interactive mouse over effects of visualizations showed details about the currently regarded information. These features were supposed to support data analysis and visualization interpretation.

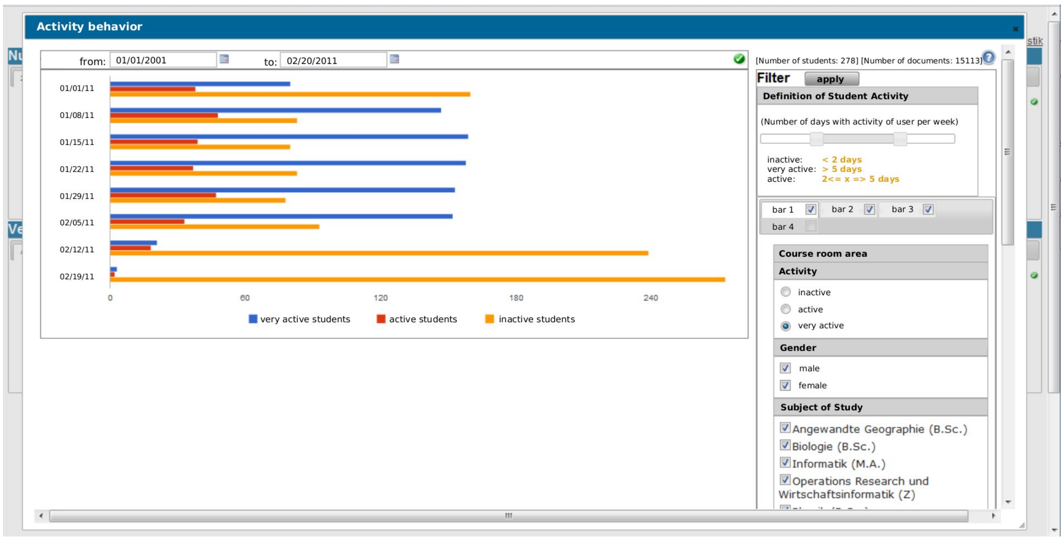

Figure 24. Analysis view of the indicator 'activity behavior'.

The link ‘Configure indicator details’ provided access to the analysis view of each respective indicator (Figure 23). The analysis view was shown as an overlay on top of the monitoring view (Figure 24). As suggested by Few (2006), layout and functionality had been designed in a consistent way to gain better usability. The analysis view was structured into an area for the indicator visualization, a top menu for parameter selection, and a filtering menu on the right side of the screen. The filtering menu allowed the user to determine, which information the respective indicator should present. It provided several options for data exploration, such as comparing the activity of male and female users, or different field of studies. The filtering options of the presented data were context-dependent according to the currently selected indicator. Later it became clear that the type and ordering of these filtering options should be the same for all indicators. Ideally, the filtering option would be consistent for all indicators.

Examples of Indicators

The following paragraphs give an overview about six indicators, which were rated to be interesting during user interviews in the first UI iteration of strand 1 and then implemented in eLAT's interface B (Launchpad).[14]

The indicator 'activity behavior' (Figure 24) is a variant of the indicator presented in Figure 20. It divides student data into three groups: 'very active students' (blue bars), 'active students' (red bars), and 'inactive students' (yellow bars). It visualizes their weekly distribution over a selected time span. An 'active student' is determined by calculating the average number of days per week, at which a student was active, i.e., logged into the system. In the configuration of the indicator 'activity behavior', shown in Figure 24, a student is defined to be 'active' if he or she logs in at least once a week. A student is defined to be 'very active' if he or she logs in on more than five days a week. The user can change the time span, and the definition of 'active students'.

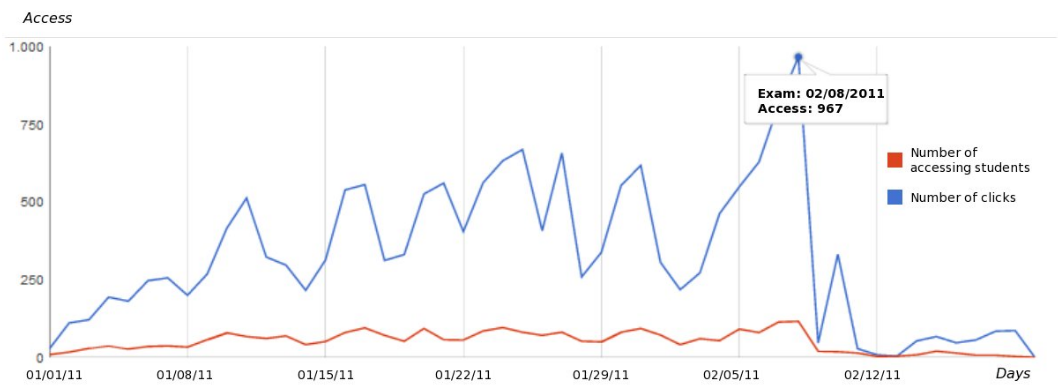

Figure 25. Indicator 'access and accessing students'.

The data in Figure 24-Figure 28 is based on a programming course, which was finished with a final exam at February 8th 2010. As expected, the indicator above shows an increase of 'inactive students' after the exam date. The indicator 'activity behavior' (Figure 24) indicates whether continuous learning is taking place. A participant of our semi-structured interviews considered continues learning as a main factor for good exam results. As a sign of continuous learning,

[14] The following descriptions of the indicators have been adapted from A. L. Dyckhoff et al. (2012).

the teacher might e.g., expect his students to log in at least twice a week to download new materials and stay up-to-date related to course information.

The indicator ‘activity behavior’ can show tendencies of increasing or decreasing numbers of active (groups of) students. High numbers of inactive students during the semester could bring the teacher to motivate his students to learn more regularly, e.g. through creating weekly exercises, or initialize further investigations on the reasons of low activity.

The indicator ‘access and accessing students’ (Figure 25) supports the teachers in monitoring the overall online activity of their course. It shows the number of accesses/clicks (blue line) over the number of unique students (red line) who accessed the virtual learning environment during a time span defined by the user. The blue line represents the sum of every single click on any resources in the learning environment per day or week. It is important for a teacher to observe if, e.g., a small group of students clicks many times or many students click once on a resource. The data in Figure 25 shows that almost every day about a third of 278 registered students accessed several resources. The peak at the end of the timeline demonstrates a strong increase in accesses before the final exam, but only a small increase in accessing students. Lines converge after the date of the exam. Probably, the students only come back to the virtual course room to check the exam results (one click per student).

The indicator ‘access and accessing students’ (Figure 25) and ‘degree of usage’ can show outliers of usual access behavior/frequency. Teachers can relate high or low usage, e.g., to teaching events or holidays. They can quickly observe if changes of learning materials or didactics lead to changes in overall usage behaviors. This might motivate them to experiment with didactics to improve the overall access to the learning environment.

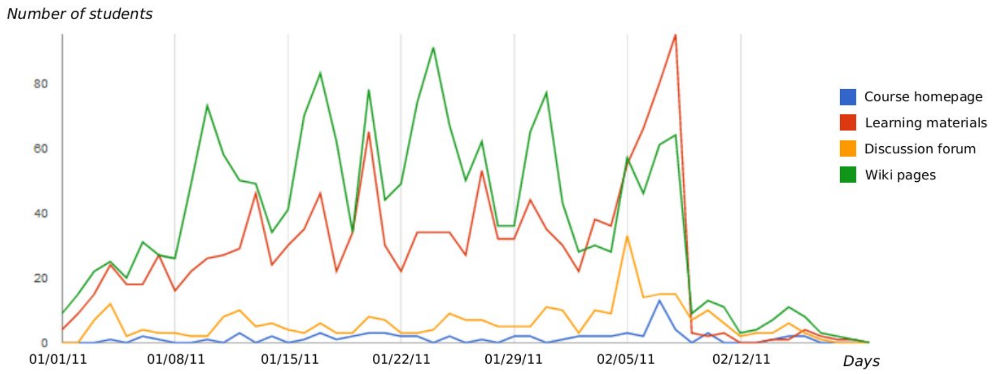

Figure 26. Indicator 'activity areas'.

With help of the ‘activity areas’ indicator, shown in Figure 26, teachers are supposed to identify whether and when students are accessing which parts/areas of a virtual course room per week in a defined time span. Hence, access rates between functions, like wiki pages or discussion forum, can be compared and related to teaching events as well. The x-axis of the indicator shows the days or weeks. If metadata on dates of course events, like the occurrence of specific lectures or the exam, are provided, these events can also be written on the x-axis. The y-axis records the number of students, who were active, i.e., clicked on resources, during that day or week in a specific part of the virtual course room. The red line in Figure 26, e.g., shows the number of students accessing a document library with learning materials, such as lecture scripts and exercises. The red line and the yellow line, which represents the number of students, who accessed the discussion forum, peak out 1-3 day before the exam. Students seem to become more active in reading and discussing during that time, so that the case could be made that they are learning more intensively.

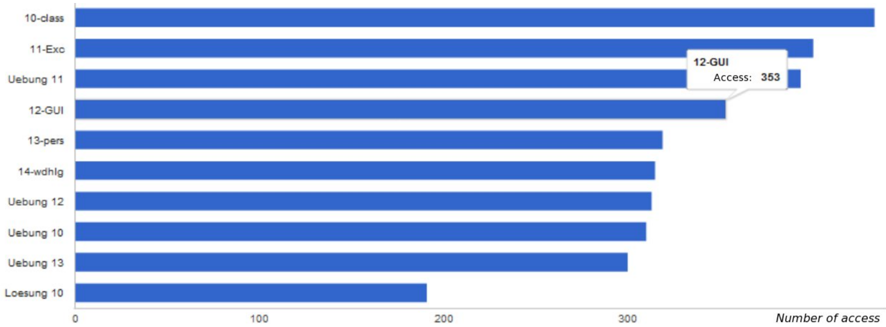

Figure 27. Indicator 'top 10 resources'.

The ‘top 10 resources’ indicator (Figure 27) gives an overview about the most accessed materials. It can help to identify active documents/items that have been accessed more than others. Such a popularity indicator could have differing reasons. A document that shows up in the ‘top 10 resources’ indicator, e.g., could be useful for solving an exercise or might be difficult to understand. The learning materials, presented in Figure 27, are exercises (‘Uebung 10–13’), code examples (‘10-class’), lecture scripts (‘12-GUI’ and ‘11-Exc’), a lecture summary (‘14-wdhlg’), and an example solution (‘Loesung 10’). This could indicate that students mainly have been learning by solving exercises. Based on this indicator, a teacher could start to explore the meaning of the high access of specific learning materials. In case of a difficulty of understanding, learning materials could be improved.

The ‘forum usage’ indicator (Figure 28) represents the number of new threads with corresponding answers to these threads (x-axis) per day (y-axis). The teacher can more easily identify increasing discussions and, thus, determine, if collaboration among students is taking place, and whether there might be problems or not. Furthermore, by looking at a thread title of the observed communication activity, problems in understanding or in preparation of learning materials could be identified. Although this indicator does not show the answers per thread it can be an activity measure for forum usage.

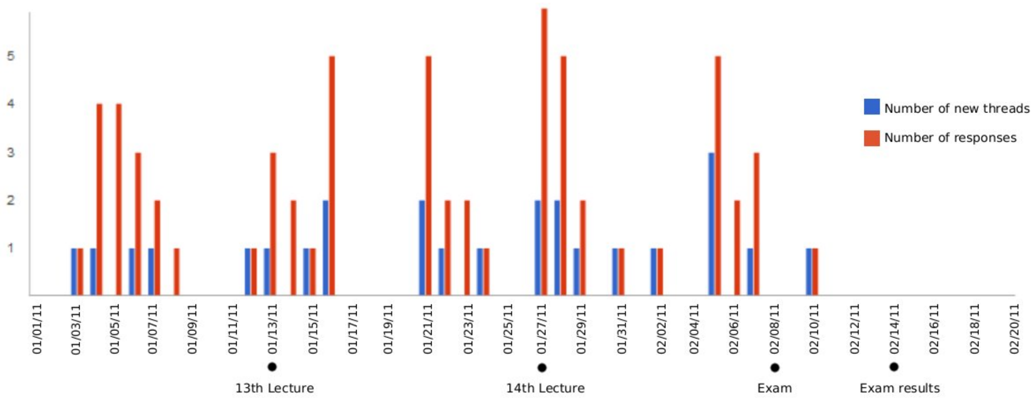

Figure 28. Indicator 'forum usage'.

The ‘adoption rate’ indicator (Figure 29) deals with the time span from uploading a selected learning material to the time of access by students. With the help of the ‘adoption rate’, it can be identified how fast how many students access new materials. It also shows the number of students who have utilized a certain material and helps teachers to find out after which time the item has achieved a sufficient distribution amongst his or her students. In some courses this is helpful e.g., because the students might have a reading assignment. Thus, teachers are enabled to estimate, how many students have at least accessed a document that they were supposed to read. If the adoption rate is lower than expected, this could be an explanation for low homework discussion participation during class.

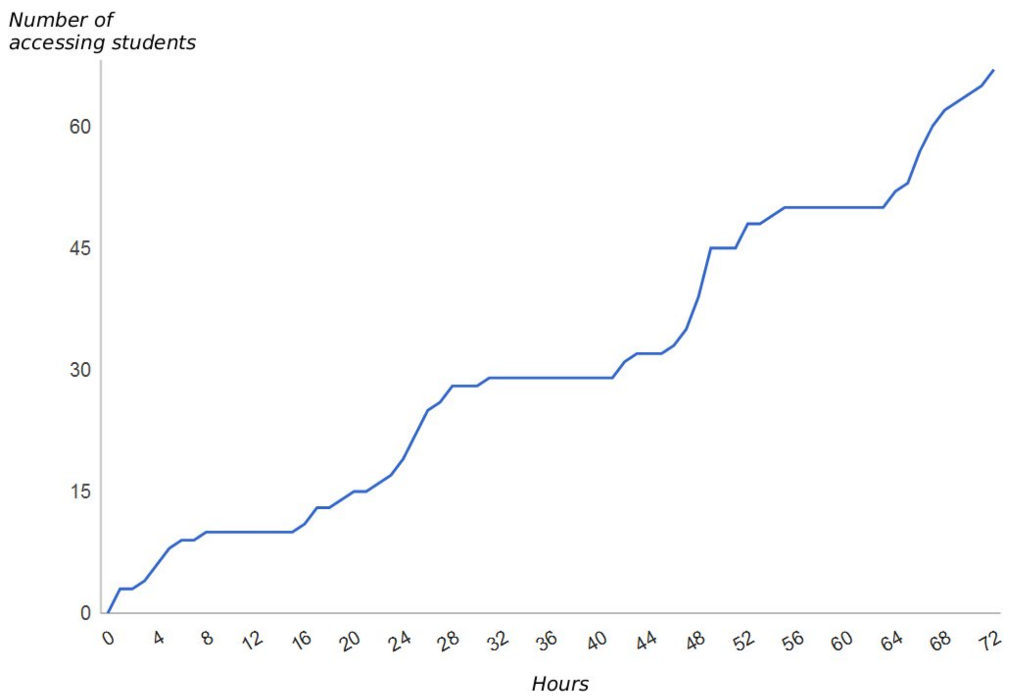

Figure 29. Indicator 'adoption rate'.

eLAT's launchpad interface was implemented and qualitatively evaluated within real courses in winter term 2012/13. The main goal of this evaluation was to investigate its usefulness and its impact on teachers (see chapter 7). However, this evaluation also revealed remaining deficits regarding personalization, question-based indicator selection, and possible integration within a VLE, which were tackled by the final UI iteration.

6.5.3 eLAT User Interface C (Question-based Launchpad)

The third main user interface was more intensely concerned with personalization and the support of questions-based indicator analysis, as characteristics of AR suggest (see section 4.2.2).

Regarding personalization, every user has different interests and needs her own configuration. This is based on several factors. First of all, there are different types and sizes of courses in higher education, such as lectures, seminars, labs and individual thesis supervisions, to be supported by LA. Each course type can in turn be organized differently. In one event, for example, e-tests are offered, in the other there are no exercises at all, but in the next there are lecture videos and exemplary exam question, but no sample solutions, and another one is very collaborative. Depending on the scenario, the teaching and analytics goals are therefore different. Also, teachers do not look for specific indicators, but more naturally ask questions. This is because the teachers' questions primarily are arising from the educational scenarios and not so much from the available data sources. For the teachers, it is therefore useful to find their own questions in the system and rather get guidance for analysis procedures; e.g., by recommendations for appropriate indicators for their specific questions.

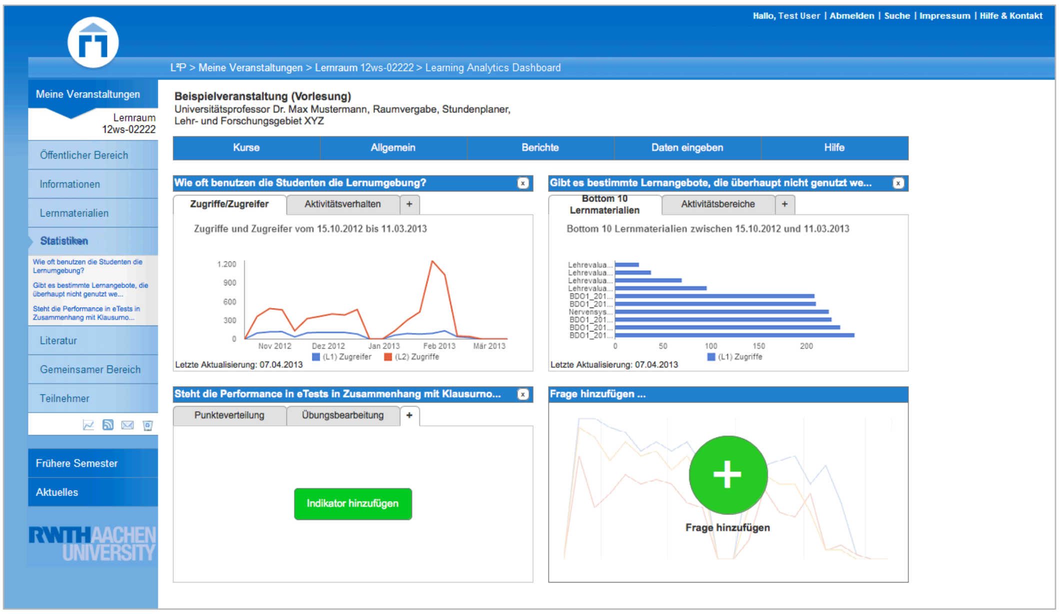

Figure 30. ARLA's interface - composed of question-based widgets.

For this reason, the interface C was mainly composed of question-based widgets, which showed the question in natural language in the title (Linden 2013). In addition, higher flexibility in terms of the adaptability of the interface was implemented within low and high fidelity prototypes, and evaluated. Basically, the former launchpad structure of eLAT User Interface B (Launchpad) remained. Appearance and placements of the indicators, however, were more individual. The new design focused attention towards the questions of a user. Each indicator was therefore associated with one or more question. A question was not necessarily associated with only one indicator. Indeed, there are several questions that can be supported by sets of indicators because, there are often several possibilities, which data to analyze and which visualization to choose.

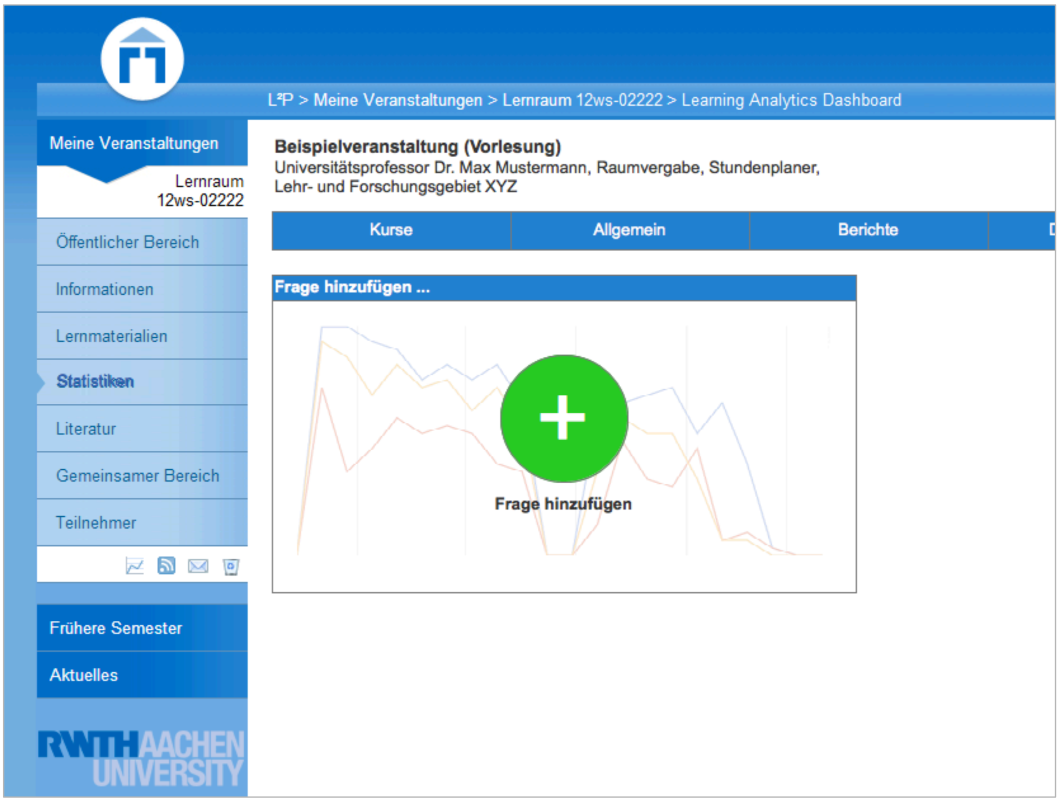

Figure 31. ARLA's first screen.

Paper prototyping resulted in the following UI design, which is discussed in form of a use case: An LA beginner, who first logs into the system finds an example visualization in his LA dashboard, as a background image of the clearly exposed option to add his or her own questions (see Figure 30). These individual questions can then be entered in natural-language text into a search box, which appears after clicking on an “add question”-button (Figure 31, “Frage hinzufügen”). Once the first words are entered, the system matches[15] them with the list of available

[15] The matching process was predefined during the development of our prototype, but it could be enhanced by using natural language processing algorithms.

questions and proposes items that are similar. Besides, the user has the opportunity to view the list of all available questions and search for interesting items. If this list is very long, it should be searchable and structured with appropriate categories, whereby some questions could be assigned to several categories. Therefore, each question should be associated with a category. Furthermore, some users want to add all questions to their dashboard and delete irrelevant questions later during the analysis step. So, it should be possible to add all questions to the dashboard with one click.

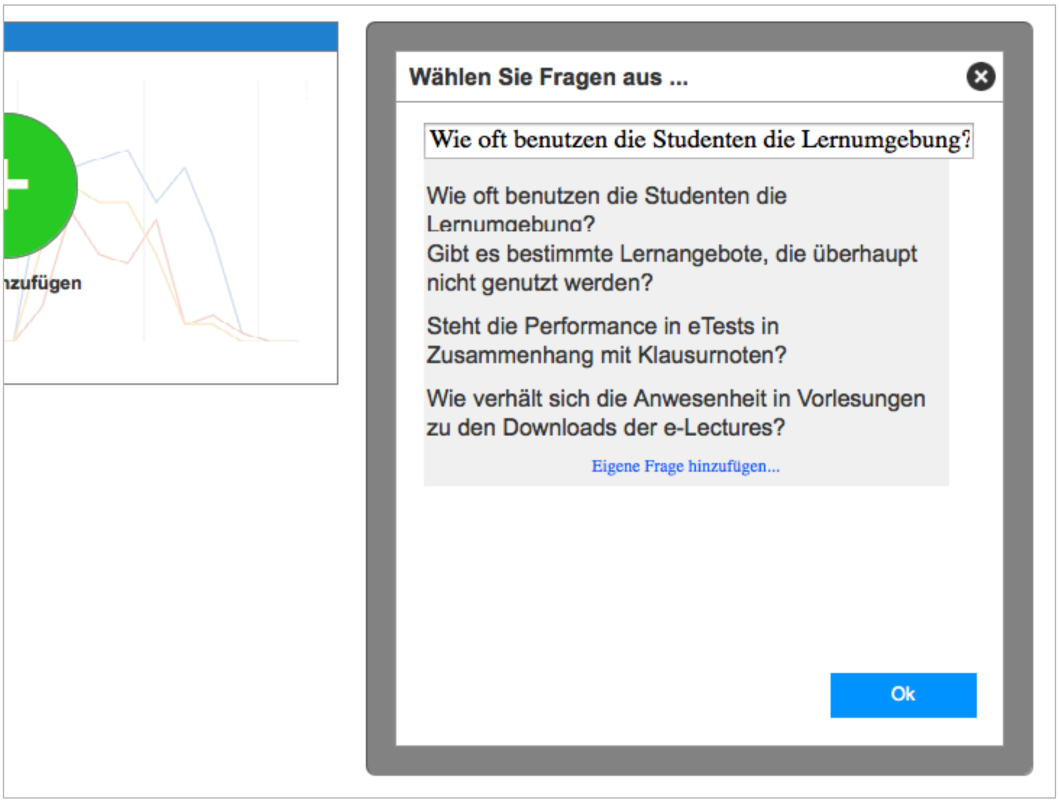

Figure 32. ARLA's questions selection process.

Those questions, which a user likes to have in his or her dashboard, can be added one by one or in a bulk. If a user has a question that is not supported, there is either the possility to request it from the indicator developers team[16], or he or she types her question, stores it, and searches among a list of already implemented indicators for suitable matches. If suitable indicators for the new question are available, the user could map them onto the question, and also share it with other users in the overall catalogue of questions.

[16] However, in this case, there needs to be such a team, and the provision would be associated with waiting time.

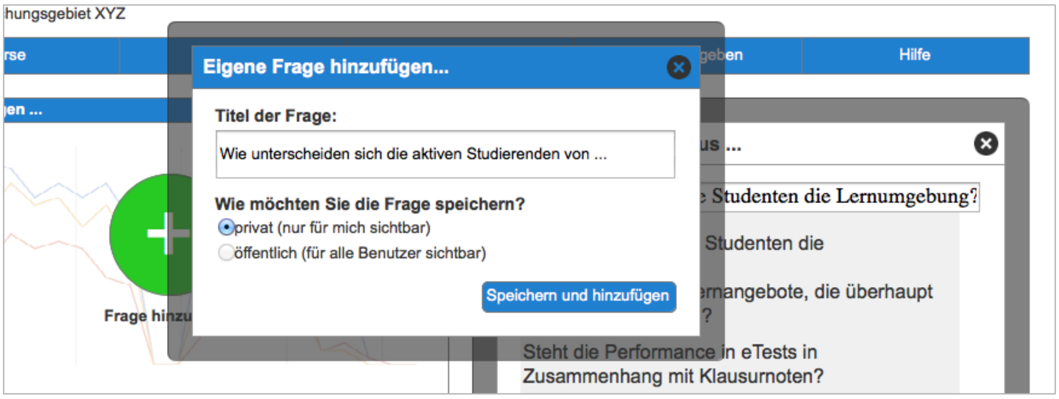

Figure 33. ARLA's popup window for adding a new question.

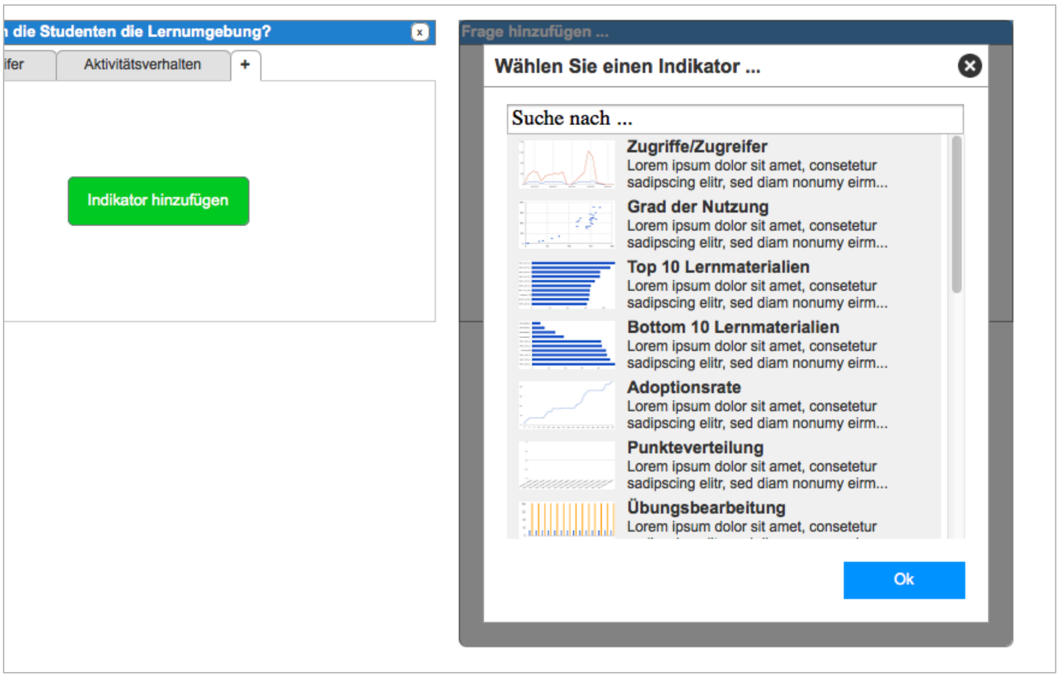

Figure 34. ARLA's indicator selection process.

If a user has finished compiling individual questions, he or she can start working with his or her dashboard during the semester. During this time, still more questions can be added or removed. Moreover, the questions can be arranged on the dashboard according to principles of widget standards.

The process of adding individual questions and their corresponding indicators to a dashboard is quite similar to an app store principle. Driven by mobile technology developments and their interface designs, modern platforms that lay focus on personalization and openness often provide users with the opportunity to select information and applications from larger lists (app stores) or even create their own apps and make them available for others. Hence, 'question-based LA apps' could also be integrated into these open platforms and allow for flexible integration of analytics, wherever a user needs them. Hence, users would be able to arrange personalized LA dashboards within open VLEs or directly integrate LA nuggets (questions) into their personal teaching and learning environment (e.g., other modules of the VLE or mobile devices).

When monitoring the visualizations during the semester, users also want to have features to explore the data. Considering the ARLA interface described above, users can access larger presentation of the indicators just by clicking on the diagrams. This opens a more detailed analysis view (see Figure 35). This analysis view can include several options for exploring the data more intensely than just having a glance at it (monitoring it). There should be filters to decide which kinds of data should be presented in the visualizations. E.g., these filters could allow for the selection of timeframes, properties of students (like gender, field of study, etc.), specific folders or documents, and etc. Furthermore, it should be possible to make notes on thoughts and findings and capture specific parts of the analysis results for later usage or share it with other (e.g., colleagues or students). At the same time, all these features and visualizations of different indicators should be summarized regarding the particular question that had been asked in the beginning. This way it is easier to compare the outcomes and create an overall picture for the answering process.

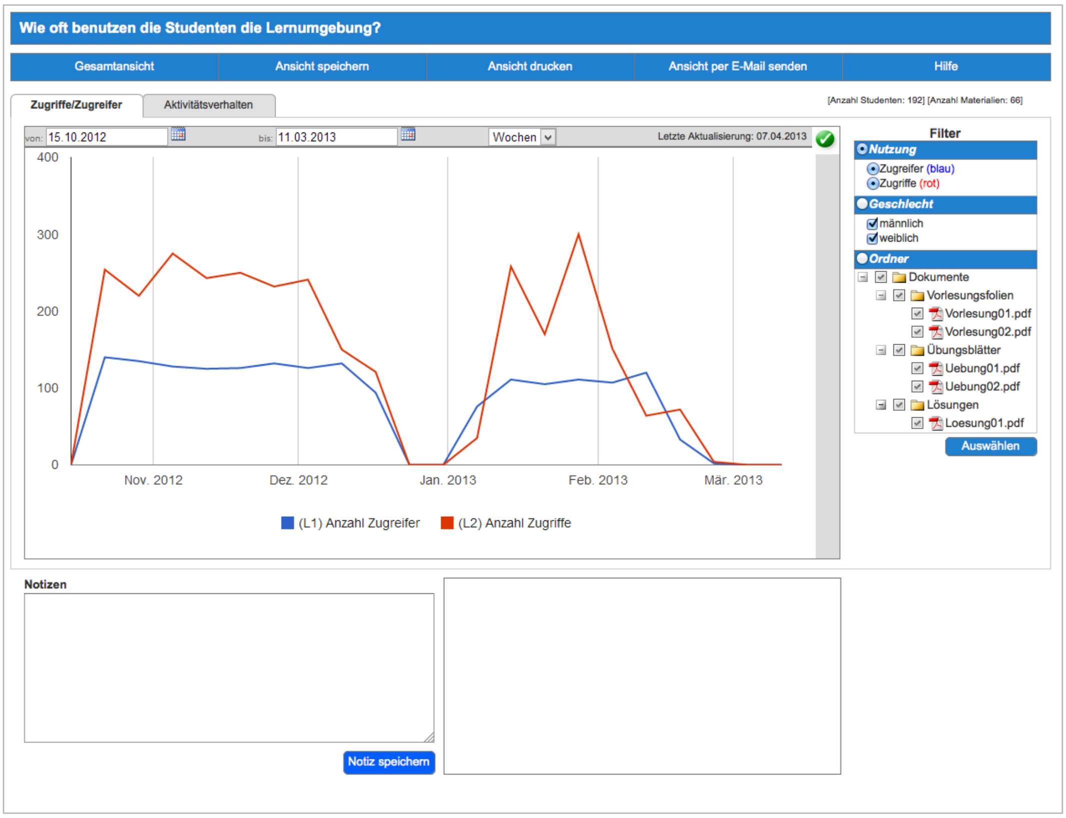

Figure 35. ARLA's analysis view.

The ARLA interface does not only provide indicators regarding one data source, but also allows for manual data import. If a teacher, e.g., would like to correlate data on how many students attended each lecture with the summarized usage data of lecture recordings, she could take notes about student participation during the actual meeting and then upload this data to the LA tool. Figure 36 shows a screenshot of the prototype on this process. The image in the background presents an indicator that is demanding new manual data input. The second screenshot below depicts an example spreadsheet for entering the corresponding data.

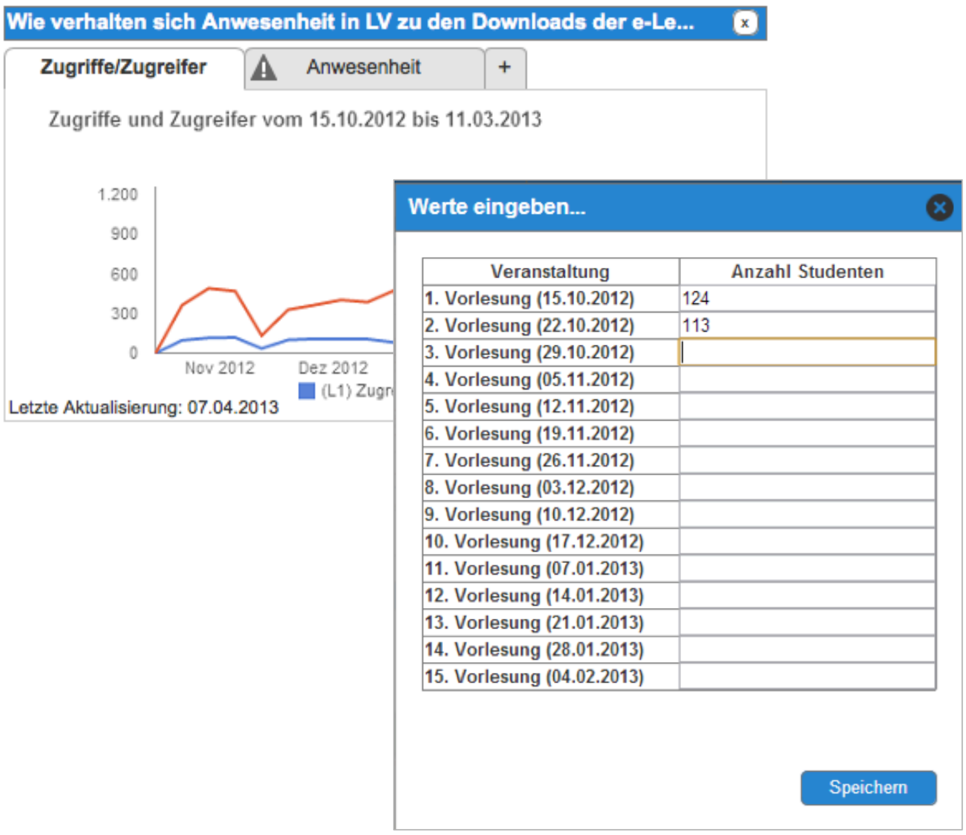

Figure 36. ARLA's manual data input.

The above described requirements for the interface – namely the introduction of filtering mechanisms, personalization, question-based collections of indicators, manual data input, and flexible integration into different VLEs – were based on findings of an evaluation, which is presented in chapter 7.

6.6 Conclusion

This chapter presented the design and implementation process of eLAT: an exploratory LA Toolkit that enables teachers to monitor and analyze their teaching activities. The main goal of eLAT was the improvement of teacher support with graphical analytics, which are useful because they allow extending the audience to teachers without prior knowledge in data mining techniques. Having a mature prototype in early stages of the development process for user tests that are based in real world scenarios was a great challenge of the design process. Paper prototypes were somewhat helpful, but also in many aspects too general because they did not represent concrete data of users' courses. Therefore, we needed LA implementations that could handle real data. With the help of the different interfaces of eLAT, teachers were supposed to be able to explore, reflect and evaluate teaching interventions based on their own interests:

- Interface A was wizard-based. It led the user through the process of parameter-selection before the outcome of the indicator-calculation was visualized. However, it was not designed for quick access.
- Interface B was designed as a launchpad. This launchpad design included a monitoring view, which united indicators of different categories on one screen, and analysis views, which provided different filtering options for each indicator.
- Interface C also adopted the launchpad metaphor, but it focused on personalization and question-based task design. Hence, users could personalize their starting page (the monitoring view) by selecting and arranging those questions that were interesting for their particular course.

The impact of eLAT needed to be evaluated in real world scenarios. Chapter 7 presents the method and findings of such an evaluation, followed by the introduction of the final ARLA model and architecture (chapter 8).

7 EVALUATION

Disclosure of previously hidden processes, encouragement of reflection, and improvement of teaching and learning have been considered as an essential motivation for the analysis of educational data. LA tools are intended to give teachers new insights into the different worlds of learning and behaviors of their students. This in turn should enable them to examine current assumptions, to verify or revise and adjust their teaching according to the needs of learners. However, the achievement of goals, such as 'awareness', 'reflection' or 'action' have not yet been satisfactorily evaluated, as shown by Dyckhoff et al. (2013). This is mainly due to the difficulty of measuring the impact of LA tools. Furthermore, increased communication between researchers and practitioners is of critical importance in order to guide the development of new LA tools and techniques (Siemens 2012b). "*Practitioners need tools that are easy to use and that provide a positive end-user experience.*" (Siemens 2012, p. 5).

Desurvire (1994) describes the difference between usability and usefulness, in other words 'impact', by stating that "*usability is more focused on the user and machine*" and *"[u]sefulness is more focused on interaction between the user and machine, as it facilitates the goals of the organization. These two concepts are not orthogonal; rather, they overlap*" (p. 200). Various LA projects evaluate the interface design of LA tools, but few studies deal with the actual usefulness of these tools, which actually creates impact (see chapter 2).

The central research questions of this thesis led to the development and refinement of several prototypes (see chapter 6). Each prototype version was studied regarding its usability and further requirements. Design science and evaluating prototypes was the basis for collecting and comparing experiences regarding different designs of LA tools. But besides the iterative development and optimization of the final artifact, there was also a need for the selection of appropriate impact evaluation methods.

Measuring impact is a challenging task. For instance, the academic field uses diverse quantitative impact measures, such as citation counts and journal impact factors, in order to measure the importance of certain publications. In the case of LA, we can also measure how often users have used specific features of our tools. However, this still does not reveal, if it influences their awareness, reflection, or fosters actions.

The impact method, which was needed in order to measure to which extent the goals of eLAT had been reached, needed to be suitable for intensely observing the usage of LA in an actual teaching context and detecting individual signs for

- teachers' awareness of students behavior and diversity,
- reflection of teaching quality, and the
- potential for initializing 'action research'.

Measuring these aspects of the potential impact of eLAT required broad knowledge and gathering of information on possible factors, which might influence the observed users and contexts. Relevant data needed to be collected and each individual teaching context of the participants had to be considered. These considerations as well as the objective to explore real world scenarios emphasized the need for qualitative methods. Also, the number of potentially participating courses in the study was small. Quantifiable answers to predefined questionnaires were not advisable in such a context because there was not yet enough experience available, regarding the way LA usage is influenced by user profiles and contexts and how it itself might influence its stakeholders. Hence, semi-structured interviews in combination with a pilot phase and user tests were chosen to be the most suitable and flexible way to collect the intended data. Indeed, these methods helped to explore the usage and effects of LA in an open way. Exploring narrative descriptions (user stories) of what happened, when eLAT was used in a real world scenario, revealed answers to several questions, such as:

- *How are which users reacting to (certain features of) the tool?* For example, we assumed that LA beginners would rather use the LA monitoring view. We wanted to find out, if they also could be initialized to analyze further by manipulating filters in the analysis views of indicators. Another hypothesis was that participants with many years of teaching experience could be less motivated to incorporate LA tools into their lectures because they might be more secure with their learning designs than younger staff.
- *Which aspects of the tool are meaningful to whom?* This question was related to the meaningfulness of indicators. Our assumption was that the design of a course and the way the VLE was used would influence teachers' focus of interest in particular visualizations and data.
- *How do the users use the tool for reflection and action?* We expected that they would generally appreciate the LA results as a good feedback, and we assumed that they would start to reflect about teaching and learning processes, if indicators would show unexpected data.

Furthermore, we were interested in finding other influencing factors for a more or less successful LA experience.

7.1 Evaluations Methods and Analysis Techniques

Our procedure for evaluating the impact of LA has also been presented by Dyckhoff et al. (2013) at the international conference of LAK'13 as well as during a DeLFI 2013 workshop on LA (A. L. Dyckhoff, Lukarov, Chatti, et al. 2013).

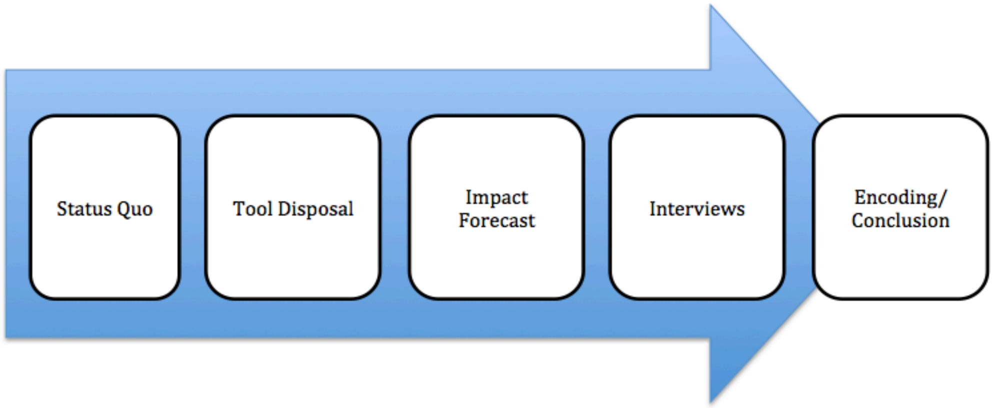

Figure 37. Five Steps of the impact analysis.

The evaluation consisted of five main steps (see Figure 37)[17]:

1. *Status Quo*: First, the situations of the real courses as well as the attitudes and plans of the teachers were collected before the tool was placed in disposal. This included, e.g., the collection of assumptions/hypotheses or questions of teachers: Which assumptions did they have about students' learning behaviors and usage of learning materials? This documentation was done by means of questionnaires or interviews, depending on the participant's preferences.
2. *Impact Forecast/Hypothesis*: Then we approximated how the tool could actually influence and change the thinking and actions of the users regarding their previously recorded contexts. In order to do this, we analyzed the 'status quo' data closely. The predictions were captured via short descriptions of potential use cases that we wanted to look for within the final analysis.
3. *Tool Availability*: The tool was then made available for a longer period of time. The target group was enabled to access it in the context of real teaching and learning situations, and data of their own courses was made available to them. During the evaluation run, storing all report requests gave an overview about the actual usage of the tool.
4. *Interviews*: We could not determine from the log data of the evaluation run, whether and to what extent the LA tool had actually encouraged

[17] The contents of the following paragraphs - until the use case descriptions – are translated and enhanced from A. L. Dyckhoff, Lukarov, Chatti, et al. (2013).

awareness, reflective thinking, and action. Therefore, it was necessary to enter into direct contact with the participants. Semi-structured interviews were a useful method for this purpose because they helped to respond individually to the users answers and stories. They also gave us insight about internal thought processes and usage intentions of the participants.

5. *Conclusion*: Finally, all the collected data from each person and event was consulted for evaluation. The audio recordings of the interviews had to be coded and analyzed in terms of the research questions.

The advantage of the above-described approach was that the evaluation results were closer to reality than results of laboratory experiments could have been. However, not all external factors were controllable, when working with real data in a real-world learning environment. We also had to deal with unforeseen difficulties, e.g., we did not meet our real-time requirements during the pilot study (see section 6.1). This is a known trade-off of prototyping (Nielsen 1993).

We documented the progress of the evaluation and intermediary results carefully. The final data analysis followed a grounded theory approach (Corbin and Strauss 1990). Audio and handwritten notes recorded the interviews. We coded the data in several ways. Two researchers tried to generate understanding from the data both deductively and inductively (Berg 2001, p. 246), in order to derive patterns from the data. Data collection and first analysis proceeded simultaniously as interrelated processes, and all data was analyzed multiple times. Based on this, ideas, resulting from the analysis of previous interviews, informed the design of question in following sessions. After the last interview, a final analysis of all data was conducted. The analytics process also influenced the ideas, the development, and the refinement of the ARLA model, which has been described in chapter 5.

The final analysis was performed in three main stages of coding, as discussed by Corbin and Strauss (1990):

1. *Open coding*: At first the transcripts of each interview were examined closely, labelling different phenomena. Also we tried to discover and name categories. Additionally, theoretical ideas from the literature regarding ‘reflection’ were used to create categories.
2. *Axial coding*: Then relationships of categories were explored for connecting them. We examined the context of each label and asked ‘what influenced this?’. Furthermore, a process description and a model of the relations was created.
3. *Selective coding*: After defining the core categories, which are central for answering the research questions, user stories were constructed around these by relating them to the other categories.

The following sections give more concrete details on the data collection of the impact analysis, present the resulting user stories, and draw conclusions based on the findings.

7.2 Impact Evaluation in WS'12/13

The impact evaluation was conducted according to the method described above. It took place in the winter term 2012/13 (WS'12/13). The aim of this study was to make statements about the extent to which eLAT's User Interface B (Launchpad, see section 6.5.2), which was the most current version at that time, can influence the behavior and thinking of teachers. We randomly selected and contacted 20 large courses (>100 students) of different faculties at RWTH Aachen via email. The number of registered students for each course had to be more than 100, because of data privacy concerns of the university's data protection officer. Supervisors of six courses agreed to participate.

During the initial contacts via email the teachers were only informed about the general procedure of the investigation. The goal of the study was not communicated to participants in advance.

eLAT was available to the participants about 8-10 weeks, starting in January 2012. Before the participants had access to the LA tool, they were asked to answer a 'status quo' questionnaire with nine questions, which we asked, in order to get to know their course design in a structured way:

1. Please name important learning objectives of your course in the form of bullet points.
2. Please briefly elaborate on your course structure. What tools, activities (e.g., lecture, exercise sessions, weekly reminders, and midterm/final exam) and materials (e.g., films, scripts, work sheets, literature) are there to assist students in learning?
3. According to your course structure: How is the ideal learning behavior for a student? How do you recognize a successful/weak student?
4. How important are communication and collaboration (e.g., by using the discussion forum) related to your course design?
5. Would it be interesting for you to have means for observing the actual learning behavior of students during the semester? Please, briefly explain why.
6. How do you identify your most effective and attractive learning materials, and the ineffective ones (which can be possibly omitted)? Are there signs that you can detect in order to realize that something is not functioning the way you expected it?
7. Are you aware of the current student behavior in practice? In your experience, are there students who show different behavior patterns than expected? What general learning strategies can you observe?
8. On what kind of observations to these experiences rely on? How do you tell that it is the way you have described above?
9. How do you address your conclusions based on your observations? Are you aiming to achieve improvement with these actions? If so, how?

As the questions above demonstrate, we collected information on course goals and materials. Also, the questionnaire included questions, which provided us with background knowledge on assumptions that teachers have, and why they designed their course in a certain way. This was supposed to help us compare course designs and teachers' mindsets with the measured LA impact; e.g., in order to study, if users, who like eLAT, have different initial situations than users, who do not find it useful. Especially, the last three questions of the status quo questionnaire, were supposed to tell us, which tactics the participants have for observing students' learning without LA, or in addition to LA. Also, we planed to analyze, if the LA pilot phase experience would change their minds with regard to previously measured assumptions.

Dependent on the wishes of the participants, they could answer the questionnaire by writing us an email or arranging an interview. Two participants chose the interview option for the status quo data collection. We sent the interview notes to them afterwards, so that they could confirm that everything they had said was recorded as they stated. The analysis of this status quo documentation gave us an overview of each participant's context, such as learning objectives, course plans, tools and materials used.

Table 13. General information about the participating courses in WS'12/13.

Interview no.	UC1	UC2	UC3	UC4	UC5	UC6
Teaching role	TA	P / AP	TA	P	TA	TA
Gender	F	M / M	F	M	M	M
Faculty	5	1	6	1	Fraun-hofer	5
#Years Teaching experience	2	20	-	22	1	5
Analytics experience	basic	no	basic	3 years	no	basic

In January we reported the provision of the tool to the participants by email. In February we contacted them a third time by e-mail to schedule an interview. Five interviews were conducted in German and one in English in late February and early March. They were conducted within the field, i.e., in the participants work environment (e.g., their office). We audio recorded each interview because this was an unobtrusive way to capture all statements. In the phase between providing the tool and conducting the interviews, we were able to identify the usage of eLAT only by the number of indicator request records in the database. These numbers were verified during the interviews by asking each user to estimate his or her usage frequency.

During the pilot phase, we discovered that the system was not performing well on the server, which we had used. In some occasions users had to wait several minutes until the dashboard was completely loaded. This problem was solved by a moving eLAT to another server. However, the participants of WS'12/13 could not benefit of this improvement. This problem was represented also in the data collected by the interviews and we considered it within the interview analysis.

Table 13 shows general information about the six evaluated courses in WS'12/13. The second interview (UC2) was carried out with two participants. Two out of seven respondents were female (2F / 5M). Four of the interviewees were teaching assistants (TA), two were professors (P), and one was an assistant professor (AP). They worked in different institutes from four different faculties of RWTH; namely Faculty 1 (Mathematic, Informatics, and Natural Science), Faculty 5 (Geo Resources and Materials Engineering), Faculty 6 (Electrical and Computer Engineering), and a Fraunhofer Institute.

The pilot courses had between 150 to 750 students. Exercises were held parallel to lectures. The submission of solutions was not obligatory for the students in four of the cases (UC1, UC3, UC5, UC6). All courses used RWTH Aachen's teaching and learning portal L²P to upload learning materials, such as lecture slides, exercise sheets, or old exams. One course also uploaded lecture recordings (UC4). The discussion forum and wiki pages – integrated functions in the learning portal – were activated in all course rooms (standard setting). However, only the teachers in UC4 used them actively, but for static information instead of collaborative activities.

7.3 Use Case Descriptions

The use case descriptions are structured as follows. First, a summary presents the main aspects of the respective use case. Then 'Course Description and User Profile' briefly describe the results of the status quo analysis. Then follows an 'Impact Forecast'. Subsequently, in the 'Pilot Phase Review' and 'Improvement Suggestions' the results of the interviews are presented in more detail with citation examples. Finally, there is a use case specific discussion in relation to the research questions.

Furthermore, the 'influencing factors' of the ARLA model, which have been introduced in section 5.2.3, are used where appropriate, e.g., for summarizing the main points. The respective factor in brackets (*factor: value*) highlights its occurrence and its value within the more detailed use case documentations. This is supposed to demonstrate how their values informed the interpretation of the data. Also, it shows exemplary how they can be used effectively for coding qualitative data in future evaluations.

7.3.1 Use Case Scenario 1 (UC1): Impact on LA Beginner

Summary

Experience, knowledge, and assumptions: A female TA is supervising a lecture. She is an LA beginner, but she already has gained experiences with learners and has assumption on how certain groups of students are learning during the semester, e.g., weak students learn shortly before the exam. During the LA activity, most indicators meet her assumptions.

Satisfaction with course: (unknown)

Way of using tool: She uses the LA tool spontaneously, unfocused, and tries out every feature/indicator. A surprising situation during the semester could have impact on her behavior immediately. Evaluations at the end of a semester could rather influence the designs of future courses.

Level of surprise: If the indicators meet her assumptions, she keeps calm and continues monitoring the data. But if something does not fit with her assumptions she is quite surprised. Depending on the plausibility of the reasons she finds by reflection, she either continues the monitoring activity or starts analyzing. Furthermore, her reaction is influenced by the time during the semester (way of using tool).

Involvement, interest, curiosity, and lack of interest: She likes the features of the analysis view, uses them to answer questions after a surprising situation, and shows increased interest in the tool the longer she knows about it and uses it.

Tool reliability: When using the tool, the TA did not like the long loading times and she received an error message, which prevents her from using the analysis view without being pointed to it again.

Trust in LA tool: Although there was an error, she still trusts the LA tool, but the loading times keep her from using it very often.

Support, qualification: The TA receives some help and explanations during the interview session. She gets to know the analysis view this way.

> ***Impact***: Observing the data presented by eLAT confirmed several *assumptions* and experiences of the TA (awareness). The LA tool also initiated *reflection*, analysis activities, and has shown the potential to facilitate *action* in future courses, if being available during the semester.

Course Description and User Profile

This course on 'fundamentals of material science' was a typical lecture, which took place twice a week, together with a large group exercise meeting for all students, in which a tutor demonstrated how to solve exercises. Additional there were small group exercise meetings with individual supervisors (tutors), office hours for individual questions, and an exam at the end of the semester. Students were allowed to hand in solutions to weekly exercises voluntarily in order to receive feedback. Learning materials were provided in the VLE. The teachers provided different kinds of learning materials, such as lecture notes, problems/assignments, slides and some sample solutions.

The research assistant had been working for two years as the manager of the exercise course. She was responsible for organizing the weekly exercises parallel to the lecture, supervising tutors, and organizing the exam. She had no clear idea about the meaning of the term 'learning analytics'. Also, she stated about herself that she had not made any analytics experience so far (*experience: LA beginner*). However, she had used spreadsheets (e.g., MS Excel) for laboratory analysis and exam statistics.

In her opinion, students optimally should continually be studying and, therefore, hand in exercises during the semester. In her opinion, continuous learning and an ability to ask complex questions would distinguish successful from weak students. Weaker students normally begin studying shortly before the exam and only ask questions about fundamental issues (*assumption: weak students study only shortly before exams).* She was interested in the observation of students during the semester in order to provide good support. But in her experience, there are many students, who do not care for her assistance during the semester. Hence, many of them consult her just before the exam with many basic questions (*experience: many basic questions before exams*). To prevent this, the small group exercises had been introduced in recent years.

Impact Forecast

Before the pilot phase, we estimated which of the available indicators could be of particular interest for the user. Due to the course description, the user's duties and her assumptions about the students' learning, we suspected that she would be particularly interested in observing the students' behavior and access to all the resources. Also, indicators about exercise course participation and question content analysis could have been interesting to her. But since this kind of data was not available in the VLE, these types of indicators could not be tested during the pilot phase. Therefore, the impact forecast was only made with regard to critical incidents and surprised reactions concerning different resource access statistics.

Pilot Phase Review

The teaching assistant stumbled upon the new LA tool every few weeks, when she was working with the VLE anyway (*way of using the tool: spontaneously, unfocused*). When asked to what extent she had used it, she said[18]: "*Actually, it was spontaneously. Just like: 'there is this tool, and I want to try and just look what it can show me; if it is meaningful for me. But it was not really tightly focused.*"[19] Her main interest was related to the questions: How many students dealt with resources and exercises, downloaded them, and used them for preparing lectures? She stated: "*It was actually quite nice to look how many people were involved with exercises and downloading them and so on. At one point, there was ONE discussion in the discussion forum, which was actually used. But mainly [I was interested in] observing, if people are preparing for exercises.*"[20]

The eLAT dashboard showed her some interesting things, though unfortunately, it had long loading times, as she mentioned several times during the interview (*tool reliability: performance issue*). In particular, she was interested in access to learning materials and exercise documents. These metrics were available in eLAT's top left dashboard area. The interpretation of the data in the indicators was easy for her in most cases. However, she thought the visualizations in the dashboard were too small. If it had been up to her, the focus could have been on the indicators related to access evaluations. These should also get more space within the monitoring view, so she can observe them easier. She clicked on all the different taps in the four areas of the dashboard to have a look at all available indicators. In addition, she clicked on 'Details configuration' once in order to find out what this feature is about (*way of using the tool: looking at all the indicators and trying out all features*). However, the first time she used it, a cryptic error message appeared (*tool reliability: error occurred*). She did not understand that it was an error, but interpreted it as a complex programming environment. Therefore, she ignored this area during the following sessions. Later in the interview and during the user test with us, it became clear to her that actually the analysis view (see section 6.5.2) should have been there, instead of the error message. As she realized it, she enthusiastically called it "*the actual program*" (*involvement: liked analysis view*).

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[18] The interview was conducted in German language. It was transcribed literally. The citations within the use cases of chapter 7 were translated into English, and colloquial speech was sometimes polished for readability reasons. Each original quote is placed in footnotes.

[19] Translated from: „Nee… Eigentlich war es mehr dann so spontan. So von wegen… ja da war ja noch dieses Tool und ich probier es mal aus und guck mal was es mir so zeigen kann, ob es noch was bringen kann... Aber so richtig gezielt? Nee, eigentlich nicht.".

[20] Translated from: „Dann war das eigentlich ganz nett um zu gucken, wie viele Leute sich irgendwie mit den Übungen beschäftig haben und auch gerade die Übungen auch runtergeladen haben und all so was … oder ich hab…Irgendwann gab's im Diskussionsforum auch mal EINE Diskussion, die dann sogar auch genutzt wurde, aber Größtenteils um zu gucken, ob die Leute sich auch wirklich ein bisschen auf die Übung vorbereiten.".

Most indicators that she found in the dashboard were interesting to her and the data presented there met her expectations, e.g. 'increased numbers of access before the exam' met her assumption on 'students are studying only shortly before the exam (*assumptions: met*). But for the indicator 'top 10' she was surprised that a particular exercise had the most traffic (*surprise: top 10 indicator*). She tried to explain this to herself and reasoned that this exercise may contain a harder task or that it was one of the first exercises and therefore the longest available in the system (*knowledge: hard exercise, long available*). She noticed that it was too late by then (end of semester) to investigate these factors further by asking the students some questions (*way of using the tool: at the end of semester*). However, she prognoses that, if she would have similar information earlier in the upcoming semester, she would directly ask the students about their frequent access to some materials (*involvement: potential action plans*). She would also talk to them, if they would not sufficiently prepare for the exercises. This is also the advantage she sees in the new tool. In her opinion, it allows her to more accurately observe the learning behavior of the students. She would also like to track how her students access the learning materials before and after exercise group meetings. Then, in the case her students would not prepare for the course, she could "*appeal to their conscience a bit regarding things that are more important.*"[21]

Regarding the provision of indicators that are based on the performance of students, she saw no great potential for her course. In this course, students voluntarily submitted homework for correction. Only a small number of the students (about 15 of overall 260) used this opportunity. Since she quickly learned the names of these active students, she recognized dependencies between homework submissions and exam performance anyhow and without indicator support. But in principle, such an indicator would have been interesting to her. The more she used eLAT, the more she liked it (*way of using tool: increased interest*). But she pointed out some aspects that could be improved.

Improvement Suggestions

First, the system should have shorter loading times or offer a configurable starting page. Perhaps 'statistics' would also be a better term for the tool than 'learning analytics'. However, this could sound "*dry*" ("trocken"), she said, whereby she probably meant: "*not attractive enough*". Through the conversation with her it was clear that she would appreciate more flexible UI personalization options. She wished to have larger views of the visualizations (or a zoom function). She liked the analysis view, which she only got to know during our user test, better than the dashboard view. She repeatedly pointed out: "*Yes, that THE stuff, this is great!*"[22] She also welcomed the interactive possibilities to make adjustments by using the filtering options. However, she did not need the gender filter. The analysis view contained the actual function of the tool, in her opinion. Furthermore, she brought

[21] Translated from: „denen ein bißchen mehr ins Gewissen reden, dass manche Sachen dann doch auch irgendwie wichtiger sind.".

[22] Translated from: „Ja, also DIE Sachen, wenn man da mal so richtig reingeht, sind super!".

the idea into the discussion, to integrate analytics in the VLE more closely. For example, access statistics could be shown directly on the documents section or the individual indicators could be made directly accessible by appearing as a separate subpage in the navigation of the virtual course room so that you can quickly switch to it. She would also welcome a new indicator that addresses the question of how access is limited to certain learning materials before and after certain events, such as lectures or exercises. In addition, she could imagine that the 'top 10' indicator could also differentiate documents by types or folders (e.g., top 10 exercise files). She furthermore appreciated dependencies between her own activities and the behavior of students. During the user test with her also a few other minor flaws in the use of the 'analysis view' became clear. E.g., it was possible to use completely different filters for the separate bars and lines in a chart that made no sense. In addition, users could forget to update the other bars when they change settings. At the time of testing, eLAT gave the user no hint that further settings should be changed.

Discussion
With regard to the research questions, the use case resulting from the first interview showed that the process model shown in Figure 38 is applicable to the behavior of the user (Awareness, Surprise, Reflection, Action Plan).

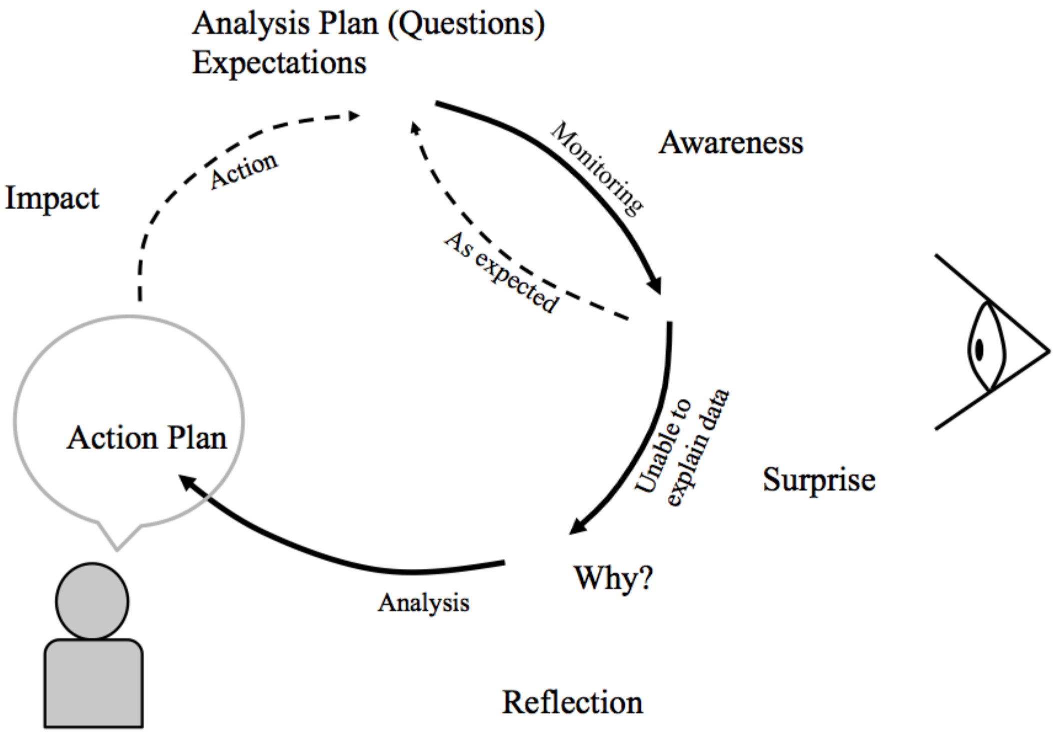

Figure 38. Expectation and reaction cycle of UC1.

A user, who teaches her course without expectations and LA experiences, found a tool in her learning environment, which she used spontaneously. This mostly helped her to verify existing assumptions. In addition, the observation of students' data also brought a couple of surprises:

> "*No, actually, what was accessed the most, I did not expect it, so this was some exercise sheet, I could not have guessed that people have another look at it and work on it somehow. That was somehow surprising for me. Although, the other information was clear to me, for example also the discussion forum, when it was used and how, this I understood well, but with this top 10, I was really surprised, what was presented there.*"[23]

This critical incident provoked thought and further analysis (*involvement: increased after surprise and provoked analysis*):

> "*Yes, I've wondered why this might be, why of all things this was the most used one. Then it occurred to me that it included a relatively difficult problem. So maybe this was the reason. Although it was quite funny, but it was one of the first, probably people had accessed it back then and then again later, that's why.*"[24]

However, she was not (yet) encouraged to actively make changes to her course. But, when being asked about it, she believed that she would become more active in the next cycle of use for clarifying issues that would arise from the tool usage. In this use case, we have seen signs of reflection, after a surprising data observation described above. We also talked about the potential for taking action after indicator observations. The user confirmed the potential of acting based on data observations, when asked about her opinion. But the interview showed that during the pilot phase she only made action plans and did not act.

7.3.2 Use Case Scenario 2 (UC2): No Impact on LA Opponents

Abstract

> *Experience, knowledge, and assumptions*: A professor and an assistant professor conduct a lecture with lab sessions. They have evaluated former runs of their course with questionnaires. Further experiences rely upon

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[23] Translated from: "Nee, eigentlich das, was am allermeisten aufgerufen wurde, hab ich so gar nicht erwartet, also das war halt'ne Übung, die da wär ich nicht davon ausgegangen, dass das die ist, wo irgendwie die meisten Leute nochmal reingucken und da irgendwas bearbeiten. Das hat mich ein bisschen überrascht, ansonsten, was da sonst so drin war, das das war eigentlich immer relativ klar, auch beim Diskussionsforum, wann da was am meisten genutzt wurde, das war alles ganz gut ersichtlich, aber bei diesen Top 10, da war ich dann wirklich überrascht, was da rauskommt.".

[24] Translated from: "Ja, ich hab überlegt, woran das liegen könnte, dass gerade die irgendwie am meisten drin war. Also was mir da nur eingefallen ist, dass da eine relativ schwierige Übung drin war. Also lag's wahrscheinlich nur da dran. Aber das war schon ganz witzig, aber es war halt auch eine der ersten, wahrscheinlich haben die Leute vielleicht mal damals reingeguckt und später nochmal, deswegen.".

discussions with students and observations during face-to-face sessions. They are skeptical about LA tools.

Satisfaction with course: The teachers are very satisfied with their course because it has received good feedback of students in former evaluations.

Way of using tool: They use the LA tool only one time because they are curious, when receiving our email. They only use the monitoring view.

Level of surprise: There are several moments, where the professor is surprised by the data, but he only looks for arguments to explain, why these findings are still not meaningful for his course.

Involvement, interest, curiosity, and lack of interest: The teachers show some initial curiosity. But during their usage session they seem to lack interest in LA. Their involvement is rather focused on finding evidence, in order to demonstrate that it is not useful.

Tool reliability: When using the tool, they disliked the long loading times.

Trust in LA tool: They do not expect to find meaningful data.

Support, qualification: They ask for explanations, why some indicators were developed and how they can be used. Our answers do not convince them for their current lecture, but they admit that some analytics might provide advantages for other types of courses.

Impact: There are no signs for impact on *awareness*, *reflection*, or *action*.

Course Description and User Profile

This course was an introductory lecture for first semester biology students at RWTH Aachen University. It combined traditional lectures with practical laboratory sessions and a final exam. Three different lecturers, who were responsible for different topics, held the weekly lecture. After each lecture, students stayed for an introduction to the next laboratory tasks. Before each laboratory session, tutors randomly tested some students to check whether they had learned for the tasks. There were several resources available in the VLE, which could be used to learn for the course: a textbook, lecture slides, and lecture summaries. The VLE was mainly used for sharing documents and distributing information. The lecturers wanted to avoid discussion forum communication, because they did not have the financial resources to supervise it.

We interviewed two of the instructors: a professor and an assistant professor. Most times the professor answered our questions and the assistant professor added his thoughts here and there, but he mainly agreed with the professor's answers. In the participants' opinion, students optimally visit all lectures, take notes, and recapitulate the contents afterwards. The lecturers had made the experience that students print their slides and brought them to the lecture for taking notes (*experience: students print slides and take notes on them*). The students were supposed to go to the preliminary discussion of the laboratory session.

Afterwards, it was expected from them to learn, what was discussed there, in order to be able to pass the tests in the beginning of each lab session. It was essential to study continuously to pass the final exam. The interviewees told their students that learning in groups was useful in general. However, they did not like to use an online course discussion forum (*lack of interest: disliked discussion forum*). They considered themselves as "*not the facebook generation*".[25] During this course, a lot had to be learned by heart, and practical tasks were often handled by each student individually. The professor also anecdotally told us that communication among students frequently led to false rumors in the past, e.g., regarding exam registration dates.

When asked about his interest in observing the students' actual learning behavior, the teacher was a little confused. He stated that his students were doing what they were supposed to do (*assumption: students do what he expects them to do*). He was not interested in statistics regarding the documents usage in the VLE and stated that they could not affect changes in the way he would upload learning materials (*lack of interest: usage statistics*). He was sure that all students were downloading the resources since he saw several of them bring printed versions into the lecture (*experience: see above*). The professor and his assistant had the impression that targeted learning for exams had increased with the switch to bachelor and master degrees. Students would try to focus on the knowledge presented by the lecturer and would like to narrow it down to the contents of the exam by asking questions about it. They would wish for more compact information because there was less time for learning than in earlier years (*experiences: students want to narrow down content to exam topics/ assumption: less time for learning*). He was sure that, although the exam outcomes were quite good, students would quickly forget, what they have learned (*assumption: students forget quickly*).

Impact Forecast

Based on our status quo analysis, we expected the teachers of this course to have only little interested in using LA. But we envisioned that they could be surprised, regarding their assumption that all students download all their lecture slides because this was not the case according to the collected data. Grounded in the participants way of using the VLE only for distribution of files and announcements, we expected the usage statistics to be the most interesting for them. Because of their dislike of online communication, discussion forum statistics, we guessed that these kinds of data would probably not influence them.

Pilot Phase Review

The interview revealed several main findings: The participants were kept of from the LA tool, because of a lack of interest. They also did not find the tool and its indicators meaningful, unless it would provide them with evidence for concrete students at risks. They liked university-wide questionnaire-based evaluations or

[25] Translated from: "nicht die Generation Facebook".

talking to students better, and they were satisfied with the learning design of their course and did not see the necessity to change (parts of) it – although they were in general open to improvement suggestions of those students, who were actively visiting the lectures. However, they were opposed to online feedback because they feared it would evolve into a "*grumpy corner*"[26] controlled by students, who did not participate in the face-to-face lecture.

The professor told us that he had consulted the LA tool out of curiosity (*curiosity: what kind of tool is this?*). He used it only once after he received our email about the tool availability (*way of using tool: pointed to it by email*). He did not use it again until the interview because of his low interest, and because it was taking too long to load data (*tool reliability: performance issues*). He tried to get the general idea by clicking on a few indicator tabs in the dashboard. But he did not use the analysis view (*way of using tool: exploring monitoring features*). Afterwards he still felt like the data was not relevant to him (*involvement: low*). He mentioned the 'daily activity' indicator during the interview. But he highlighted it mainly as an example for his argument that the tool was not valuable to him concerning an impact on his teaching:

> Professor: "*And then I asked myself the question ...*"
> Moderator: *"... do I need this?*"
> Professor: "*What do I need to know about the circadian behavior of the students… about the times they load the files?*"
> Moderator: "*Yes, okay.*"
> Professor: "*Because it has no ... it does not affect how I provide files, whether they download them at three during the night or in the mornings.*"[27]

Indeed, when looking at indicator 'degree of usage', the professor was quite surprised that only about max. 150 of overall 192 students had accessed his script; because he was assuming that all students downloaded his materials in order to bring it to the lecture (*surprise: usage lower than expected*). The professor and the TA discussed this and several other unexpected indicator visualizations closely with each other during the interview. We could have looked upon these discussions as 'reflective discussions' from our analysis point of view. However, in the end, they always tried to strengthen their argument that the LA information was not useful to them (*lack of interest: argument, why not useful*). This pattern was observable throughout the whole interview, although they could imagine that the indicators could be interesting for instructors of more open courses with lots of files and literature suggestions, from which, not all of them are mandatory

[26] Translated from: "Meckerecke".
[27] Translated from: Professor: „Und da hab ich mir gleich die Frage gestellt ..." Moderator: „... was brauch ich das?" Professor: „Was muss ich über das zirkadiane Verhalten der Studierenden wissen... wann die da die Files abrufen?" Moderator: „Ja ok." Professor: „Weil das hat ja auf meine... auf die Bereitstellung meiner Dateien keinen Einfluss ob die das jetzt nachts um drei herunter laden oder vormittags.".

readings. So, teachers of such courses could be enabled to observe how students explore the learning materials. Accordingly, the TA stated:

> "*The distribution of learning materials is very similar to the lecture. We have the lecture, and then we have the lab preparation and the related PowerPoint presentations. We upload the related script one week earlier into the virtual course room. And people download it and bring it to the lecture. I can imagine that this is more interesting for the Humanities, when people upload 20 books and say: have a look and decide what's most interesting for you and then they receive more feedback on this. What the people really read and what they don't read? But our students actually need to download everything and take it to the lecture.*"[28]

They also compared midterm evaluation data from university-wide questionnaires and input from face-to-face discussion with students, who visit the lecture, against LA and concluded that the first two were much more efficient and effective for them than they would any LA expect to be (*experience: other evaluation methods provide more meaningful data*). Anyhow, we got the impression that their course structure was quite fixed. It had been created over years of teaching experience and the teachers were sure that it was a good course (*satisfaction with course: high*). Although they mentioned some disadvantages for minorities – e.g., it was a problem for international students that the lecture and all the materials in the VLE were in German – they argued that it was not in their realms of possibility to solve these issues, but rather a task of the exchange programs or faculty – e.g. the students should fulfill the perquisites to understand German or the faculty should decide to switch the general language of courses to English instead of German.

Improvement Suggestions
Tool performance was again an issue in this interview. An LA tool should load quickly, especially at the first time of usage. Since the participants of the interview did not have ideas on how to use the data, the interface could provide help and examples on how the data could be used. When discussing the visualizations, the professor mentioned that the views could be bigger. The discussion of longer periods of usage data also showed that it would be helpful to have important course dates/events included within the diagrams. Regarding the filtering features, the professor suggested to normalize the data. For example, in his lectures there were about 60% female students and, if the visualization show 60% more ‚clicks', this would not mean anything to him, unless the data was

[28] Translated from: "[…] bei uns ist diese Bereitstellung von Lernmaterialien ja ziemlich eins zu eins zur Lehrveranstaltung. Also wir haben die Vorlesung und dann die Vorbesprechung und die PowerPoint-Präsentation dazu. Das Skript dazu wird dann die Woche vorher in den Lernraum eingestellt. Und die Leute laden sich das runter und bringen es zur Vorlesung mit. Ich kann mir vorstellen, dass das für Geisteswissenschaftler interessanter ist, die dann 20 Bücher darein stellen und dann sagen: guckt euch das an, was euch am meisten interessiert und da dann mehr Feedback zu bekommen. Was haben die Leute dann wirklich gelesen und was nicht? Aber bei uns müssen die Studis alles eigentlich jetzt erstmal runterladen und mit in die Vorlesung bringen.".

normalized. The discussions regarding the indicator ‚adoption rate' demonstrated that it should provide the possibility to select at least one week (opposed to only 72 hours) or the whole semester. Furthermore, the discussion of the indicator 'degree of usage' led to the conclusion that the order of the data might correlate to the period of time certain documents have been online. So, the longer certain files are online, the more they are accessed. This should be considered within the indicator design and documentation. Finally, a new indicator idea was developed: the detection of students at risk. But it was immediately remarked that data privacy regulations probably would not allow for giving this information to the teachers.

Discussion
Since the teachers of this course did not actually use the LA tool during the pilot phase and since they did not find it meaningful, we cannot conclude that it would support them in being more aware about students (Figure 39). They only relied on results of standardized questionnaires or on qualitative feedback by talking to some of their students. This feedback had more impact on their teaching than LA could probably ever have.

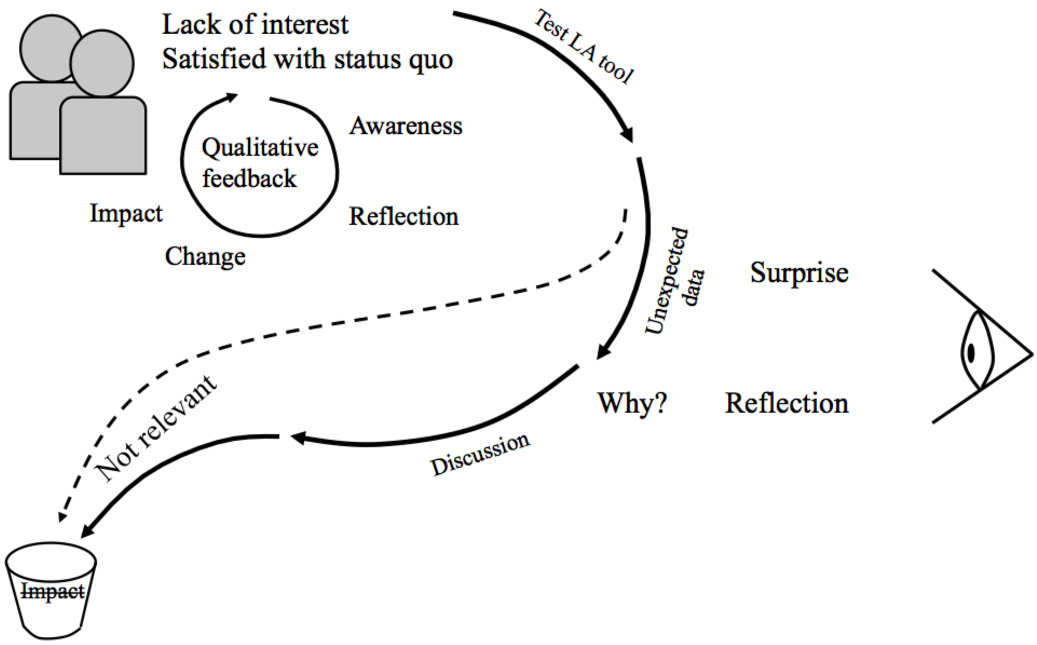

Figure 39. River of no return of UC2.

Although, we observed reflective discussions during the interview, these were rather supposed to confirm the teachers' initial arguments that the data was meaningless for the respective course. Maybe it could be useful for one of their smaller courses, such as seminars, the assistant professor mentioned shortly. To conclude, our analysis did also not reveal 'reflection' as an effect of using the tool. Moreover, there was also no 'action' based on data analyses visible or planned. Anyhow, discussions of indicators showed that outliers in the data could have been interesting, or at least had a potential to surprise and make the users think about it.

7.3.3 Use Case Scenario 3 (UC3): Impact on LA Beginner

Abstract

Experience, knowledge, and assumptions: A female TA is supervising a lecture. She is an LA beginner, but she already has gained experiences with learners and has assumption on how certain groups of students are learning during the semester. In her experience, collaboration among students is important. During the LA activity, most data meets her assumptions, but there are also several surprises.

Satisfaction with course: She thinks her learning offerings are adequate, but students' behavior is not always optimal.

Way of using tool: Her first session is initiated by our email. Long loading times impede her LA usage, e.g., they hinder exploration of the analysis view. During the analysis, she chooses different filter options, and states that she wants to use LA more regularly.

Level of surprise: She is surprised several times, especially about low forum usage numbers and the students' high usage frequency.

Involvement, interest, curiosity, and lack of interest: She is particularly interested and involved in the discussion forum indicators and the field of study filter. At the end of the interview she says that would like to use LA on a regular basis.

Tool reliability: There are performance issues with the LA tool and some diagrams are hard to interpret (usability). Furthermore, it remains unclear if there was data missing because of zero access during Christmas break. Nevertheless, she still likes the tool.

Trust in LA tool: She shows no sign for distrust.

Support, qualification: During the interviews she conducts some analyses together with the moderator.

Impact: With respect to this use case, we found evidence for *awareness*, *reflection*, and a potential for *action* based on the analytics activity, although, problems with the tool had been reported.

Course Description and User Profile

Use case scenario 3 turned out to be very similar to use case scenario 1. The course was a programming lecture with several additional activities for supporting students' learning: e.g. a '*global exercise*'[29], which is basically an exercise lecture for all students, weekly practice hours in smaller groups, programming supervision in dedicated computer labs, a discussion forum, an (online) consultations hour, and two exam dates at the end of the semester. In the VLE, there were learning materials, such as a script (commented lecture slides), weekly published exercise sheets, slides of the 'Globalübung', literature and link lists, tutorials for using a development environment, old exams, additional problems, and a wiki. The additional literature was supposed to support students, who did not have much previous knowledge.

Our contact person was a TA, who organized the overall course. She had some previous experience with analyzing data in spreadsheets (*experience: LA beginner*). In the status quo study, the TA stated that students should optimally participate regularly in lectures and small exercise group meetings. They should prepare themselves by solving assignments provided within the VLE. In her opinion, successful students would actually prepare the exercise meeting beforehand, actively participate in the group sessions, ask questions, and submit own solutions. Weak students would rather like to consume and collect all materials. But they would relatively soon not be able to understand the topics discussed in the meetings anymore and start preparing for the exam only at the end of the semester (*assumptions: how good and weak students' behaviors differ*). She rated communication and collaboration as important. Students should help each other and use the discussion forum for answering each other's questions. Allowing for building groups and submitting solutions in teams was supposed to facilitate collaboration (*experience/assumption: communication and collaboration is important*). She stated about the current situation:

> "*The offer of the exercises is only used by a few students, although it is actually an effective way to control their own learning. The interaction in small groups leaves a lot to be desired. Many students actually want to copy only the sample solution instead of working on the topic. Students who try to learn the material only in the end of the semester for exam preparation are usually not capable of it based on the large amount of information.*"[30]

She based this experience on observed participation rates in her office hours, which were mainly used shortly before the exam. Also the types of questions students asked then, showed her that many of them began to learn only shortly before the exam and did not practice programming enough (*experience:*

[29] Translated from: "Globalübung".
[30] Translated from: "Das Angebot der Hausaufgabenabgabe wird nur von wenigen Studenten genutzt, obwohl es eigentlich eine effektive Methode ist, seinen eigenen Lernerfolg zu kontrollieren. Die Interaktion in den Kleingruppen lässt manchmal zu wünschen übrig, viele Studenten wollen eigentlich nur die Musterlösung abschreiben, anstatt den Stoff zu erarbeiten. Studenten die versuchen, den Stoff erst am Ende des Semesters zur Klausurvorbereitung zu erarbeiten sind auf Grund der Menge meist nicht mehr dazu in der Lage." (Status quo).

participation frequency and question quality regarding office hours). The TA dealt with this experience by advertising the learning offerings continually during the semester. In her opinion, the learning offerings were adequate. Students just needed to use them more intensively (*satisfaction with course: course adequate, but students' behavior needs improvement*). Because of the explorative, wide base of learning offerings, the TA was interested in observing, which resources were actually used by the students.

Impact Forecast
Since the TA stated that she was interested in monitoring which learning offerings were actually used by the students, it was self-evident to foresee that she would be interested in several kinds of statistics, regarding file usage and discussion forum participation. Analytics of exercise participation and outcomes certainly could have been interesting to her, but unfortunately only the exercise sheets were published through the VLE, because student handed in their homework solutions during the weekly meetings. So, we could not automatically access the data besides data privacy concerns by the data protection officer of the university.

Pilot Phase Review
The TA used the LA tool only twice during the pilot phase; the first time was after we had written the email about the tool availability. She told us, she would have used it more, if it had had a better performance (*way of using tool: initiated by email, intended to use it more, but impeded by long loading times*). Because of the low usage, we showed the tool to her again during the interview. In her opinion, the user interface was intuitive. She had even tested the analysis view during the pilot phase, but had canceled this interaction after a while, when it took the indicators too long to load (*way of using tool: tried to also explore analysis view*).

The interview findings confirmed our assumption that indicators regarding the exercise course would have been most interesting to her. She stated: "*Yes, it would be nice if we could read the behavior of students in terms of the exercise participation, but we don't have it here in the course room, unfortunately.*"[31] Anyhow, she adjusted to this situation by planning: "*The exercise sheets are in the course room, exactly. We probably could have a look how much they have been accessed.*"[32]

The 'degree of usage' and 'top10 resources' indicators supported her in observing that the slides of the 'global exercises', old exams and a script file had been accessed the most (*assumptions: met*). Also, exercises with lower numbers, which had been published earlier in the semester, had higher access than more current exercise sheets (*surprise: very interested until reason was found*). First, she

[31] Translated from: "Ja, es wäre natürlich schön, wenn man jetzt son bisschen auch das Verhalten der Studierenden ablesen könnte, was die Übungsbearbeitung angeht, aber das haben wir ja hier im Lernraum gar nicht abgebildet leider.".
[32] Translated from: "Die Aufgabenblätter sind in den Lernmaterialien, genau. Da könnte man vielleicht gleich mal gucken, wie häufig das abgerufen wurde.".

concluded that one reason might be that the earlier exercises had been easier to solve. But a closer look showed that the number of accessing students per file was actually not varying much (*way of using tool: closer look together with interview moderator*). So, we concluded that some students accessed exercises, which had been uploaded earlier in the semester, more than once, as time passed by. The TA was also interested in analyzing discussion forum usage (*interest: discussion forum*). Especially, she asked: "*Yes, let's see the discussion forum. I'd be interested to know how many people are reading it.*"[33]

While she was analyzing the data during the interview, there were several moments of surprise. Especially, the low number of reading accesses in the discussion forum was not according to her expectations (*surprise: low forum usage*). Also, she was surprised, when the indicator 'activity behavior' revealed a higher number of very active students, who accessed the systems on a regular basis more than five times a week. This was more than she had expected (*surprise: high usage frequency*). Her reaction was to use additional indicators for checking data revelations that were not conform to her expectation. This activity was sometimes also influenced by the questions and information given by the moderators of the interview (*way of using tool: analysis together with moderator*). There were also some other surprising observations, but they were set aside/explained, when using alternative filtering options, e.g., at first we observed the highest peak of usage in January. This was a surprising moment because the TA assumed that most students would access the system close to the exam in February. But when adjusting the indicator to show the actual number of accessing students – instead of only the number of access – the graph showed the highest peak right before the date of the exam, just as expected before (*way of using tool: choosing different filter options*).

The TA was very interested in using the 'field of study' filter. She explained that students from different fields have different previous knowledge and she was, therefore, interested in monitoring, if there were also differences in VLE usage (*assumptions/interest: field of study filter*). Based on this, she stated: "*What has always interested us - but we do not get it from this - is whether the students, who regularly submit their homework, whether they perform better in the exam than those who do not regularly submit the homework.*"[34]

She also told us about trying to study this question in past semesters by using spreadsheet calculations. But there had been no conclusive evidence for stating that solving homework helps to perform well in exams. At the end of the interview and user test, the TA was interested in using LA regularly in her courses

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[33] Translated from: "Ja, wir können mal im Diskussionsforum gucken, da würde mich interessieren, wie viele Leute da überhaupt mitlesen.".

[34] Translated from: "Was uns auch schon immer interessiert hat - aber das kriegen wir jetzt hier auch nicht raus - ist, ob die Studenten die jetzt regelmäßig ihre Hausaufgaben abgeben, ob die natürlich in der Klausur besser abschneiden als die, die nicht regelmäßig die Hausaufgaben abgeben.".

(*involvement/interest: wants to use LA regularly*). It would be important to her that an LA tool supports her to be aware about information that has not yet been noticed by the students enough, in order to be able to influence the situation. Overall, she felt like the information presented by the indicators mainly met her expectations.

Improvement Suggestions

Our discussion with the TA uncovered remaining usability problems and a few bugs. Besides mentioning necessary performance improvements (*tool reliability: performance issues*), the TA suggested to more clearly describe, what is presented by some diagrams' y-axes. The difference between 'number of accesses' and 'number of accessing students' was also not always clearly visible to her. This led to temporary misinterpretations of the data (*tool reliability: usability*). The user test also revealed that the 'adoption rate' indicator would be more useful, if it showed a larger time frame – instead of only 72 hours. When one indicator showed unexpected results, e.g. not even a single access during Christmas break, the interview moderators themselves expressed their suspicion, if the data collection had been working, as it should (*tool reliability: missing data?*). We drew the conclusion that LA tools need to be reliable and users need to be able to trust the information presented by them. Finally, at the end of the interview the TA stated that she would like to have a feature for comparing data of different courses and semesters in the future.

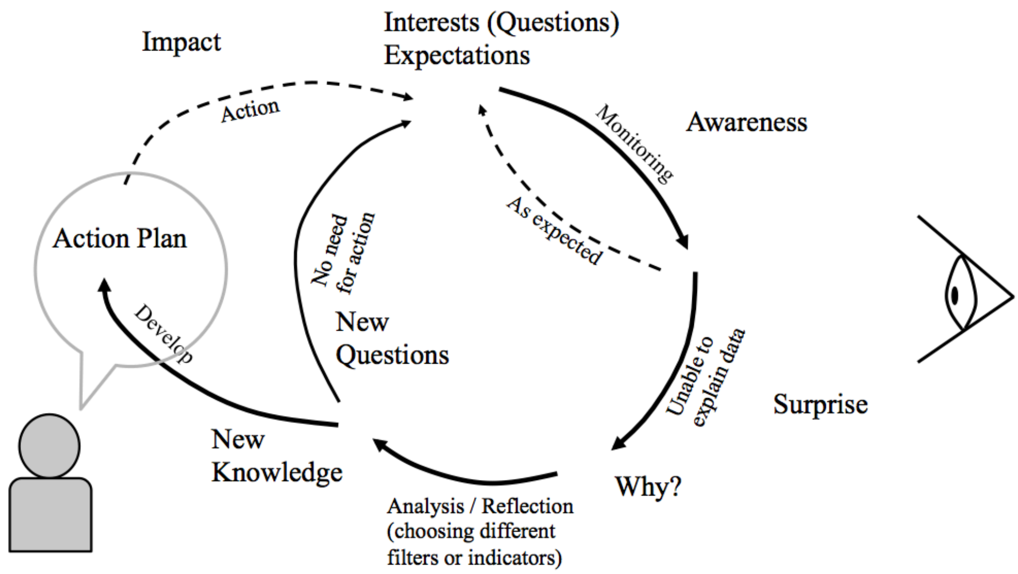

Figure 40. Expectation and reaction cycle of UC3.

Discussion

Using the LA tool helped this participant to check her assumptions, but it also led her to formulate several new questions, which could not all be answered by the available indicators. Some of the questions were related to surprising insights into the access behavior of students (e.g., high login frequency and low discussion forum access). Other questions were related to aspects of the data, which were not understood well or could not be explained at that particular moment: e.g., the 'bottom 10 resources' indicator showed a document, which was not recognized by the TA. It remained unclear, what kind of file or course room webpage it was. This finding was mainly distracting, instead of giving insight into the learning of students. We noticed during the analysis that a third of the students were accessing the course room on average more than five times a week. A possible conclusion could be that these students used external applications, which automatically logged into the VLE every time they were online. The effects of such applications need to be considered in future LA since especially mobile apps are becoming rampant.

Our analysis of this use case gave evidence for 'awareness', 'reflection', and a potential for 'action' based on the analytics activity (Figure 40). All information gathered during the monitoring activity, which was not fitting to previous assumptions, led to surprise and discussions about possible explanations (reflection). Based on this, deeper analyses were conducted in order to answer upcoming questions. Furthermore, some discoveries had the potential to facilitate further teaching activities (action plans), like writing an announcement or an email to the students in order to remind them about the discussion forum. These activities could actually impact the course and improve the learning of its students.

7.3.4 Use Case Scenario 4 (UC4): No Impact on Advanced User

Abstract

Experience, knowledge, and assumptions: The user is a professor. He is a trained TEL user and action researcher. He also has advanced knowledge on LA. In former evaluations, he has analyzed VLE data based on certain questions. He has used the findings for improving aspects of his course. He names several of his current questions. These are related to students' learning behavior, their performance, and correlations of performance with usage of particular learning offerings.

Satisfaction with course: He is already satisfied with the design of his course because he had studied and improved it in former evaluation runs.

Way of using tool: When using the tool, his main focus is the tool design, rather than the data presented by the tool.

Level of surprise: He is not surprised by particular visualizations anymore. However, he remembers surprising situations from past analytics activities and tells anecdotes about these findings. He also has shared this knowledge with colleagues and the TEL research community.

Involvement, interest, curiosity, and lack of interest: He tells us about his general interest in LA. But he shows a lack of interest in data about the current course, which is presented by eLAT.

Tool reliability: He provides us with a list of improvements suggestions based on the tools user experience.

Trust in LA tool: (unknown)

Support, qualification: He needs to be reminded about the structure of the tool during the interview, because he does not remember directly how it looks like and what it presents.

Impact: Although, he is an advanced user, he uses the tool only out of curiosity about its design, not for really analyzing his own course. We cannot find signs for actual surprise or action. When asked about it, he states that there are no needs to further optimize the particular course that was analyzed with the help of eLAT.

Course Description and User Profile

This course was a programming lecture, which was specifically designed for students from different fields of study (non computer science students). Additional to the weekly lecture, there was an exercise course with weekly assignments. These assignments were published before each topic was presented in the lecture, so that students were able to have a look at them beforehand or bring them to class. After the submission deadline, the professor and his assistants provided sample solutions. Furthermore, there were several interactive tests within the VLE for students to test their theoretical knowledge. The teachers also provided different kinds of learning materials, such as slides, lecture recordings, literature, etc.

The professor, who answered us the status quo questions by interview, had 22 years of teaching experience. During the second interview, he also stated that he was reflecting on what he was doing for the same length of time (22 years), and he knew about the concept of AR. He was also the supervisor of this thesis. This specific situation was considered in the conclusions of this evaluation.

The participant described the ideal learning behavior of a student in the following way: Students are supposed to keep up to date with all learning activities of the course. So, they should solve assignments in time and they should study continuously. He wanted to observe the behavior of his students in order to detect patterns (*interest: How do they learn? What are good learning activities?*). The professor also mentioned that he wanted to correlate usage data with data related to success in midterm and final exams (*interest: correlations*). He thought, it might help him to find out, which materials are most used or whether students like the learning resources. Furthermore, he wished for summaries of students' performance data, and wanted to correlate this data with other data, in order to answer the overall question: How do different groups of (good, medium, bad) students study? (*interest: classification of students by performance*)

His previous attempt to collect data regarding his questions was the introduction of paper-based questionnaires into his lectures, or to talk to students after oral exams. He had tracked the usage of the VLE, manually analyzed this log data with spreadsheet tools, and improved course elements in former settings. From all participants of our study, he therefore had the most experience with LA (*experience: advanced LA experiences*). He did not only use the VLE for resource distribution, but additionally incorporated interactive online content into his course. So, compared to some other users, he was using the VLE in a more advanced way (*experience: advanced TEL user*). Lastly, the participant stated that he was explicitly interested in analyzing data in order to answer questions and improve his courses in an action research-like way (*interest: action research*).

Impact Forecast

We knew this use case well, when forecasting the impact of LA on it. We also knew that data analysis had helped the professor to perform changes on his previous course designs, which had had observable impact on students' online behaviors. Furthermore, we could not provide indicators based on performance data, which was explicitly requested by the user, because of data privacy regulations, which could not be solved before the pilot phase started. Therefore, we were not sure how to predict the impact of eLAT on the users behavior. Since he was motivated and comfortable with LA, we assumed that he would appreciate to have access to it. We estimated that he would be able to answer some of his research questions in a more efficient way than before. However, we foresaw that he would miss some indicators about performance measures.

Pilot Phase Review

The professor stated that he used the tool two to three times during the pilot phase. But his primary focus was the examination of the tool rather than analyzing the data presented by it (*way of using tool: get to know tool*). He also contacted us, after using it for the first time, in order to give us feedback in a timely manner, i.e., he sent us a list of notes on how to improve the interface. His first tool usage session took about two hours, which might be due to his goal of getting to know the tool.

In the concluding interview he confirmed that his interest in analyzing data about his courses was generally high: "*Well, it's quite high. I would be interested to find out things about my lectures. That's why think it's a good tool to look at different data and try to answer questions and find questions, I can't answer with surveys or something.*"[35] However, in this particular use case, his interest actually seemed to be not that high (*involvement: low*).

[35] This interview was conducted in English. Therefore, there was no need to translate this and the following citations.

The professor mentioned the objective to "*find questions*" several times. It is likely that he meant, 'checking, if there are problems', 'generating new questions', or 'being inspired, which questions to ask' during the process of analyzing data based on indicator results that are hard to explain with previous knowledge.

When we asked him about the quality and his thoughts on using the tool, he was not sure, if he remembered everything, and therefore he pointed out his notes, which he had provided us with a few weeks earlier. For this reason, we gave him a short overview on eLAT's design to remind him of how it was structured. Then we asked him to actively use it during the final interview, and to tell us about his thoughts. He started to follow this task by saying: "*Ok… Well, actually, right now I have no question and I'm not prepared to really analyze anything. Which would be interesting to do. [...]*" This shows that he felt a little awkward to begin an analysis without concrete questions in mind (*way of using tool: with questions in mind*).

In the following think-aloud situation, it became clear that he felt neutral towards the observed data. There were no surprising situations, when consulting the data (*involvement: low*). But he anecdotally told us about past moments of surprise (*surprise: not now, but in earlier analysis sessions*). One surprise was, e.g., his detection of low usage of sample solutions. This had led him to successfully change the overall timing of the exercise course. His course redesign activities increased the access statistics regarding sample solutions in the following semester.

As predicted, he missed particular indicators related to students' performances and correlations of usage and performance. He stated:

> "*Yeah, so actually …and I think, and that's what I was looking for, but I didn't find my notes so far, I have many… if I have concrete questions, I need more correlations between the ones who have been good in maybe certain assignment or some of assignments… How did they look at specific things? So usage of things correlated to some performance measure. Whatever the performance would be like. Points in assignments or maybe 'Zwischenklausur'… 'Hörsaalübung' as we call it here. So… and things like that. So activity or usage correlated to performance or specific activity. That would be the most interesting for me to look at. But the single indicators can be interesting, just to scan through them and have a look and then find something surprising. I don't know in this case here now, but when I started doing that, I found out that a lot fewer students would look at the slide casts, as I would have expected. Because always, when I ask the students, they say that's the most important. That's the best what we want to have. And then you look at it and its only 10% usage. So that's surprising. And so it's good to have some single indicators to look*

> *at them and say: 'Hey, I expected something else here!' And then you can start researching that.*"[35]

Indicators for correlating data would help him achieve his analysis goals. However, as the statement above shows, the "*single indicators*" – a term that he used for indicators that do not correlate different kinds of data – can also initialize analysis activities in his experience (*experience: indicators initialize activities*). He ascribed this initializing effect, especially, to data, which is not conforming to the expectations of an LA user.

The last sentences of the citation above mentioned a connection between a surprising situation, expectations, and the initialization of research activities. We had observed this pattern also in previous use case findings. It informed the development of the ARLA process model (see section 5.2).

When the professor was telling an anecdote about the low usage of slide casts by students, he mentioned a situation of 'sharing his findings with colleagues':

> "*Yeah. And this is my experience and that WAS surprising for me 3 or 4 years ago before we developed these tools. And I think that's ... and this shows, its worth to look at those indicators also for other lecturers. I know it already. This time I'm not surprised, but I was surprised a few years ago. And still, if you discuss that with colleagues, they would say: 'No, no, no, slide cast is most important. Students love slide casts.' They want to have them. So it would be good for them to look at it, because that's proof.*"[35]

This user story revealed that he shares his knowledge and likes to use LA results as 'proof'. However, it also points to the danger of generalizing and translating one experience to situations that might not be comparable.

Improvement Suggestions
During the final interview, there were two key improvement suggestions. First, he wished for correlation indicators. Second, he recommended giving students access to LA:

> "*[...] Let have students… give them the tools and work with. And then correlate their own behavior to other groups. As mentioned again, maybe they have the four groups of performance and how they behaved and then compare their own behavior to the ones ... and maybe having profiles of …'I'm somebody, who is collecting slides every week as do the others', so maybe you compare behavior and how they… what is their performance and then maybe have recommendations how to behave for students.*"[35]

The discussion about 'giving LA to students' resulted in the suggestion to make it possible for students to compare their own data to others, but not to force them to do this, if they do not want to compete with others.

Further improvements suggestions had been handed to us in written notes. He asked for similar UI improvements as the other users, e.g., he recommended to increase the size of visualizations, to provide zoom features, create flexible, responsive dashboard designs, and implement support for saving or sharing analysis outcomes with colleagues.

Discussion

The participant of the use case described above had a special role within the context of the research at hand: He was supervising this thesis, and he therefore had background knowledge about its goals and methods, as well as a personal interest in its positive outcomes. Furthermore, the professor had made individual experiences with AR methodology. Hence, this situation certainly influenced his answers. Nevertheless, his use case was included in the study because it gave evidence and possible answers to the questions: How might more experienced TEL users and AR practitioners be influenced by LA? And what kind of implication has this for the design of related tools?

A central analysis category, which emerged within the coding process of this use case, was that this more experienced user was not surprised of the data presented by the tool. This was due to the fact that he already had found reasons for all kinds of data constellations based on previous LA cycles, which he had conducted manually. Several times, the professor mentioned that he had experienced surprises based on data analysis outcomes, when first doing research on this particular course, but not during our pilot phase. He also had the feeling that the course was well designed and optimized at the time of our evaluation. He was satisfied with the course design. Although, he described himself as motivated to do AR, he actually was not motivated to do it in this particular situation. He told us that their had been no time during the semester to concentrate on using the tool more than he did. When asked about his reaction with regard to the data, he told us:

> "*Ok. I'm quite emotionless. So not happy or unhappy… I'm interested in it. And I try to find out the information. What does it mean? What does it tell me? Ok … So I'm quite neutral because I say, ok, this is factual data, let's have a look at it and then make sense of it. So that's what I feel about it. It's just… emotionless.*" [35]

When asked, how he interpreted the data, he stated:

> "*Well, as mentioned before, at first I just look at it, scan through it, and try to find out, whether I can see anything surprising or maybe see, ok, these are high numbers, these are low numbers, and then I start from that to make sense of it. So to form hypothesis and then maybe have a more detailed look into things or then maybe I just try to find some correlations, if I can look at this and this and then, does it make sense? So I try to find questions.*" [35]

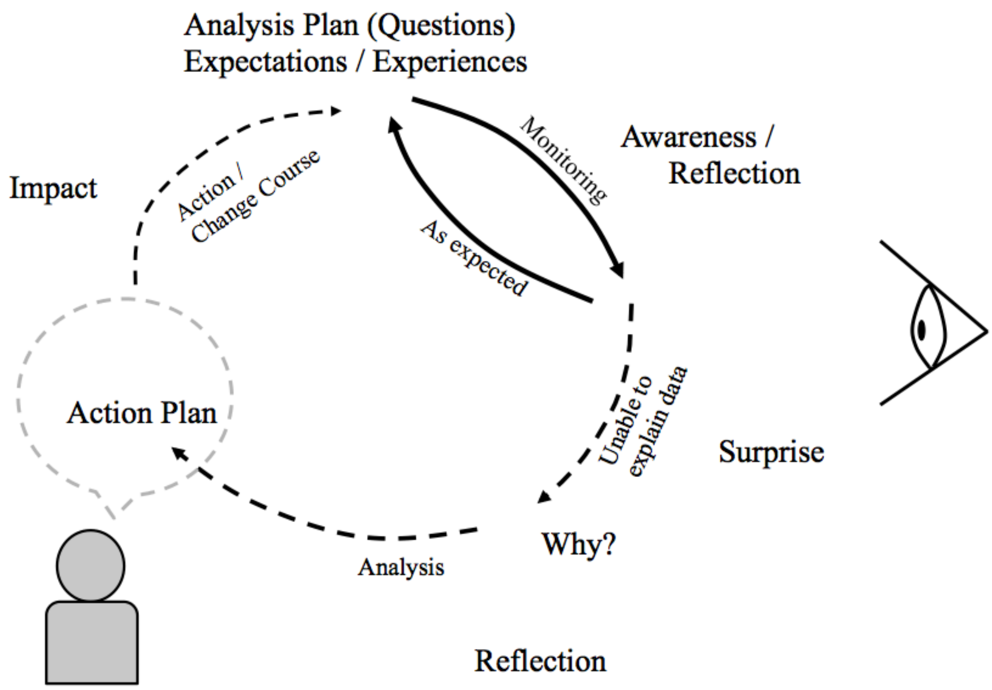

Figure 41. Expectation and reaction cycle of UC4.

This statement actually described his LA usage process (Figure 41). He pictured himself as monitoring the data and waiting for surprising revelations. He was looking for extremes and outliers of data, e.g., high and low numbers, and trying to make sense of them by finding reasons. If he could not explain an observed problem he called this "*to find questions*". This term could be related to his AR knowledge.

We also talked about the influence that LA could have on his awareness and teaching. He said:

> "*Yeah, well it has some impact on awareness because if I have the data, let's say <finger flip> at my finger tips always, like, and I can have a quick look. Now, what we did before, was kind of hard work because we had to dig all the data and try to find out about the slide casts or to find … find out about how we… I told you the story also with our assignments model that we shortened that phase and then we had some impact. So it influences what we do for the next term, if we can find out things and see, ok, here is something wrong, or here could be something optimized. Then we try to adapt our model.*"[35]

A follow up statements was:

> "*I mean, the question was also: 'Does it influence me, having it available?'. And I think that's the point. It's there and maybe, if I look at*

it, and I don't even start with my question maybe, but it's there and maybe I have a look at it and then I could be initialized … motivated to do more. It might motivate me. I'm a bad example because I'm already motivated and I'm already working on it, but still I think, it might even influence me to have a more constant look at data." [35]

Also he stated:

> "*I think, having it available and I mean I'm working in the course room twice a week anyway, so I'm here 'oh let's have a quick look' I can imagine that's why it could motivate to even to some more action research than before. Before, I really did it on purpose. So I'm, ok, now I want to optimize something. I want to find out something. And then I have to think about what to do. And there it could motivate me to just constantly do it.*" [35]

The statements ascribe the advantages of 'availability' and 'quick access' to LA. If the LA tool additionally reveals a surprising problem situation, this can initialize active improvement processes similar to AR. However, AR is a method with requires active involvement and it is a systematic approach (see section 4.2). The phrase "*Before, I really did it on purpose.*" implies that LA activities might be conducted without clear intentions. So, the constant availability of data could be a drawback compared to his original way of systematically collecting data for analysis based on questions. But it also could initialize the development of new questions that he did not ask before he had looked at the tool.

A farther pattern, which emerged, was the importance of meaningful data in reference to improvement activities. However, 'meaningfulness of indicators' seemed to be dependent on users' previous experiences as well as on the course designs. The professor's previous knowledge and assumptions encompassed low levels of surprise and involvement in this particular use case.

7.3.5 Use Case Scenario 5 (UC5): Little Impact on LA Beginner

Abstract

> *Experience, knowledge, and assumptions*: This male TA has no experience with LA and has been coordinating his course for about one year.
>
> *Satisfaction with course*: (unknown)
>
> *Way of using tool*: He uses the tool the first time after reading our email and two other times spontaneously. His usage is focused on the monitoring overview (dashboard).
>
> *Level of surprise*: The data of the indicators are not always as he expects it. He feels uncomfortable and is surprised, but since he does not really trust the prototype, he does not reflect further about possible reasons.

Involvement, interest, curiosity, and lack of interest: He is only interested in simplified access summaries, such as the number of students who have logged into the system at least one time. But he also likes some filtering options.

Tool reliability: He does not like to wait for visualizations several minutes.

Trust in LA tool: His level of trust in the tool is very low because it is a prototype. This might have been influenced negatively by the long loading times of some indicators.

Support, qualification: The TA explicitly wishes for short online tutorials for each indicator because he feels that explanations on how to use them could help him a lot.

Impact: The user wants to be *aware* about the amount of active students and eLAT helps him to achieve this goal, although he wishes for a simpler indicator with respect to his question. There is no sign for *reflection* about the course design because he does not trust the accuracy of the data collection. However, he mentions that the final tool (not the prototype) could influence his own *activities* in future courses.

Course Description and User Profile

This course was a weekly lecture with additional exercises. All learning materials were provided within the VLE. Additionally, there were lectures of practitioners, giving the students insight into practical examples of 'quality management' in industries, which was the topic of the course. For exam preparations, there were office hours and sample exam questions.

The TA was the coordinator of the lecture and the exercise course. He had been teaching for one year and had no previous experience with analytics tools or spreadsheet calculations (*experience: LA newcomer*). His teaching role was to coordinate all the people involved in the lecture and also to conduct the exercise course and planning of the exam. He stated that students should actively participate in the lecture and exercises for successfully finishing the course. It was his goal to monitor this active behavior. In his opinion, communication and collaboration among students was helpful, but not necessary for the course.

Impact Forecast

Based on the status quo analysis, we concluded that the TA would be most interested in the indicators concerned with the students behavior, e.g., 'activity behavior', which allows for defining, what an active students is and having a weekly overview on the number of active students.

Pilot Phase Review

The TA told us that he had used the LA tool about three times during the pilot phase. His first usage was initiated by our email about the tool availability. The other two sessions were more spontaneously at the end of the semester, when he was doing something else in the course room anyhow (*way of using tool: initiated by email and spontaneously*). When asked, how he would use such a tool in future courses, he guessed that he would use it on a monthly or quarterly basis, which was conform to his usage behavior during the pilot phase. He also explored the system a bit, e.g., he opened the analysis view of at least one indicator, but because of slow loading times (*tool reliability: performance issues*), he canceled to work with it. He also did not understand well how to use the filters in the analysis view, so he mostly relied on monitoring the dashboard overviews (*way of using tool: explored featured, but used mainly monitoring view*).

Overall he thought the tool was interesting, and he was mainly focused on the access statistics. Although he was skeptical about the overall number of accesses, which was lower than the number of registered students, he found that it was a good feedback to know that some students were actually accessing the materials (*surprise: uncomfortable feeling, data does not meet assumptions*). His main question was: How many students access L²P at what times? He told us:

> "*I looked at it at times and I found it really quite interesting ... the statistics on access were the most exciting. Especially for us as a feedback that people access it. However, I'm a bit cautious in total with the results that came out of it because the number of participants is significantly higher than the access numbers and I so am a bit skeptical because everyone is - so my expectation would be that the students use the L²P at least once - I am accordingly not quite sure if everything was recorded.*"[36]

When asked about his reaction, he also said: "*I was especially surprised because numbers seemed to be very low*".[37] However, since he assumed that every student would at least login once and since he knew that the system was a pilot, he did not quite trust the unexpected results (*trust in LA tool: low*). He concluded: "*To be honest, I thought: this is a test phase, who knows if everything is really recorded.*"[38] His distrust distracted him from reflection about his teaching on several occasions during the interview.

His main goal was the planning of the course. LA feedback was supposed to tell him how many students were active learners, e.g., because he wanted to estimate how many students would come to the exam. Therefore, he was not interested in detailed visualizations. We talked about a new indicator, which was described as a

[36] Translated from: "Ich hab ihn mir mal angeschaut und ich fands eigentlich ganz interessant... die Statistiken über Zugriffe, die fand ich eigentlich so mit am spannendsten. Auch so für uns mal als Rückmeldung, die Leute greifen drauf zu, wobei ich in Summe etwas vorsichtig bin mit den Ergebnissen, die dabei herauskamen, weil die Teilnehmerzahl deutlich höher ist also die Zugriffszahl und ich deswegen so ein bisschen skeptisch bin, weil jeder sich ja – also meine Erwartung wäre gewesen, dass die Studenten den Learning Analytics, also das L²P überhaupt mal nutzen – entsprechend bin ich nicht so ganz sicher, ob da alles erfasst wurde an der Stelle.".

[37] Translated from: "Ich war vor allem erstaunt, weil die Zahlen mir sehr niedrig vorkamen".

[38] Translated from: "Also wenn ich ehrlich bin, hab ich gedacht: das ist ja ne Testphase, wer weiß, ob wirklich alles so erfasst wird.".

single bar, which presents the number of students, who have at least logged in once to access something, related to the overall number of registered students. This would be a key indicator for him to measure how many students are getting all relevant information. If this indicator would show him a low number of active students he would take action and tell students during an exercise meeting to use the VLE.

> TA: "*That is definitely an important thing. So I assume that a student who needs the learning materials... that he finds it and all is ok. At the same time, we must ensure that the students ... that we have done everything to ensure that the students have all the organizational relevant information. Then it would be definitely good to know, ok, I've ... it is now Christmas and I've of 100 students with whom I count I only have 20 or only 10 active in L²P. This is definitely an important info.*"
> Moderator: "*And then you would possibly become active and in your course...*"
> TA: *"…in the exercise meeting I would point to it on several occasions, yes.*"[39]

This example shows that such indicators would have some potential for action. The only other indicator, besides 'access rates over time', that was interesting to him was 'adoption rate'. But he only understood its purpose after we explained it to him (*support: explanation by moderator*). Then, he liked it because it might help him to 'get a better feeling', when to upload resources in relation to the times students download it. Our explanations helped him to understand the purpose of the tool and how to use the analysis view and its filters. Therefore, he suggested providing tutorials to users, which tell them what to expect of the analytics tools (*support: short tutorials*).

He showed no interest in other indicators. He argued that access rates are no indicator for the quality of learning materials, since students have to access first before they can decide, if a file is useful to them. The indicators regarding communication and collaboration did not provide any data because there was no activity in the discussion forum and wiki of his course. If there had been active participation by students, he would have been interested in these indicators.

On our way out after the interview, the TA told us that he also liked the university-wide evaluations for getting feedback regarding the quality of his

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[39] Translated from: TA: "Das ist ja auf jeden Fall eine wichtige Sache. Also ich geh davon aus, dass ein Student, der die Lernmaterialien braucht, sich ... das er die die dann entsprechend findet und das alles ok ist. Gleichzeitig müssen wir aber sicherstellen, dass die Studenten... also, dass wir alles dafür getan haben, dass die Studenten die organisationsrelevanten Informationen haben. Dann wäre es auf jeden Fall gut, zu wissen, ok, ich hab... es ist jetzt Weihnachten und ich hab erst von 100 Studenten mit denen ich rechne erst 20 im L²P oder erst 10 Aktive. Das ist auf jeden Fall ne wichtig Info." Moderator: "Und dann würden Sie evtl. aktiv werden und in der Veranstaltung..." TA: "…in der Übung noch mehrfach darauf hinweisen und ja.".

course. We talked about integrating these kinds of students' feedback into LA, and he thought it was a good idea.

Improvement Suggestions
The user test showed several issues that could be improved in the next version of eLAT. Of course, the slow performance was an issue again (*tool reliability: performance issues*). Furthermore, the TA did not have any expectations based on the term ‚learning analytics' and he sometimes confused the wordings "*accessor*" und "*access*"[40] because they look similar at a quick glance. Because of his interest towards 'usage over time', he ignored most of the other indicators. So, it might be better to have more personalized selections of indicators in order to create more space for those, which are relevant to the user. The participant also specifically wished for bigger visualizations and making filtering menus more prominent (maybe put them on the dashboard). Additionally, he wanted less granularity in the graphical presentations. Monthly overviews opposed to daily or weekly would be more adequate for his purposes. The filtering items regarding 'field of study' were most interesting to him. Furthermore, we developed a new filter idea concerned with grouping data by degree type, such as 'bachelor' or 'master'. During the usage of the filters, it took too much time to select all of them. We concluded that they should be pre-selected in a standardized way and there should be standard one-click options to select or de-select all checkboxes at once. Also, automatic adjustment of warning regarding filter selections was suggested to avoid illogical calculations. As an analytics beginner, the TA wished for short tutorials for learning how to use the tool and each indicator. And finally, a notification subscriptions counter, which shows how many students are receiving email notifications about new items in the course, was a new indicator idea besides the 'active students' bar chart indicator mentioned in the previous section.

Discussion
This use case revealed the following behavior pattern of the TA (Figure 42). He mainly wanted to be aware about the amount of active students. He was also interested in diversity filters, especially 'field of study' differentiations. Accordingly, a state of surprise was be triggered by low access statistics of certain groups of students. He stated:

> "*I think it would be most important for me to realize ... So, we use L²P not only for learning materials, but also for all organizational information; i.e., it's all about: When is the exam? When is the inspection? How is the grade distribution? So the grade distribution is there, how is it? We would like to control everything with the L²P. So, the most important statement for me is, I've got a certain amount of active students that also corresponds approximately to the amount of registered participants or*

[40] Translated from: "Zugreifer" and "Zugriffe".

not. If I don't have it, then I would have to think about it heavily. I would need to point out in the lectures that L²P has to be used."[41]

His actual reaction to the low access statistics observed during the pilot phase was to mistrust the system. He thought that it was probably a mistake of the data collection tool. A possible reason for his doubt in the reliability of the tool was the pilot phase declaration. His suspicions clearly kept him from reflecting about students learning behavior or his own teaching. So, there was no impact observed. However, he stated that normally, he would be initialized to think about the data and talk to students, in case that something was going wrong. Although he conveyed the impression in us that he feared changes in didactical plans during an ongoing course because students might not get it.

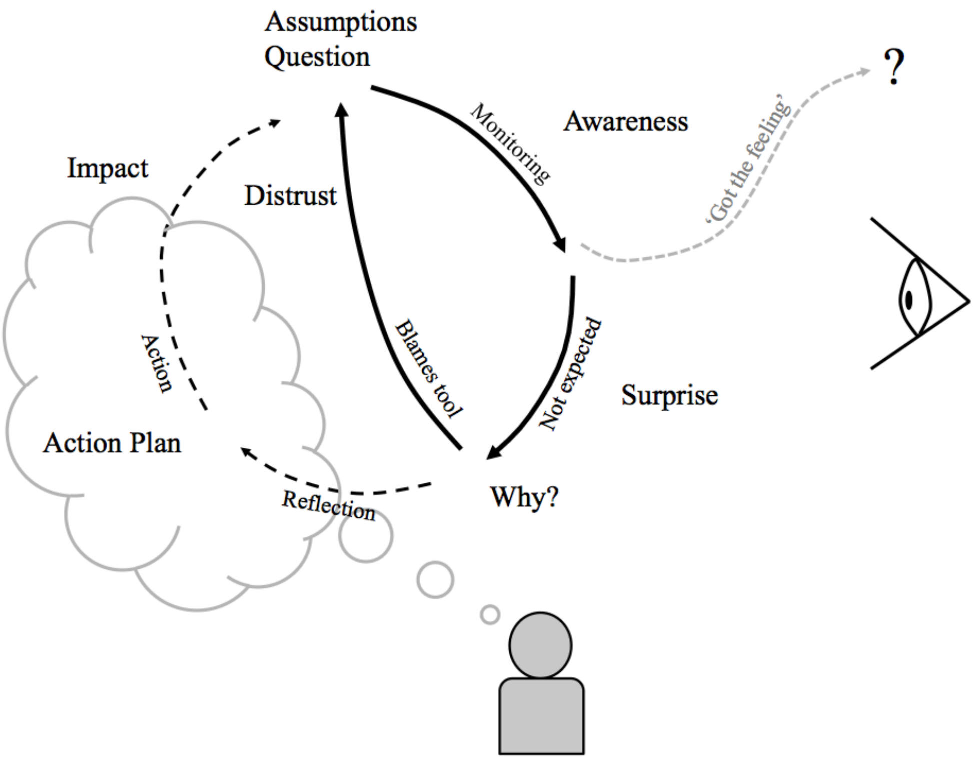

Figure 42. Expectation and reaction cycle of UC5.

During the interview analysis, we noted that he talked about "*getting the feeling*" several times, which we interpreted as 'learning how students usually behave' and

[41] Translated from: "Ich glaube, das für mich wichtigste an der Erkenntnis wäre... also wir nutzen L²P nicht nur für Lernmaterialien, sondern auch für sämtliche organisatorische Informationen drum herum. D.h. da geht's vor allem darum: Wann ist die Klausur? Wann sind die Einsichten? Wie ist die Notenverteilung? Also die Notenverteilung ist da, wie ist die? Das würden wir alles über das L²P gerne steuern. Also dh. die für mich wichtig Aussage ist, ich hab ne gewisse Menge an aktiven Studenten, die auch etwa der Teilnehmermenge entspricht oder eben nicht. Wenn ich die nicht hab, dann müsste ich mir sehr große Gedanken machen, dass ich in den Vorlesungen nochmal darauf hinweise, dass das L²P auf jeden Fall zu nutzen ist.".

‘being able to predict the outcomes of indicators’. So, we wondered what would happen, when he got the feeling eventually? Would he stop using the tool? We could not make any conclusions about this based on this use case’s data, but UC4 had given some impressions related to this. Advanced user might ‘get bored’ with looking at the same indicators again and gain. This finding will be explained in more detail in the overall discussion and conclusion (see section 7.5).

7.3.6 Use Case Scenario 6 (UC6): Some Impact on LA Beginner

Abstract

Experience, knowledge, and assumptions: The male TA of this course has used some analytics tools unrelated to LA before.

Way of using tool: He does not really use the tool during the pilot phase because of an error in the first trial session. But he prepares for the interview by having a look at it again.

Level of surprise: The user reports a moment of surprise regarding the access to course information. After reflecting on it, he concludes that the low numbers are related to changing the files name during the semester.

Involvement, interest, curiosity, and lack of interest: He is interested in the LA tool, but performance issues hinder him to actually use it.

Tool reliability: The performance issues prevent the user from using eLAT during the pilot phase.

Trust in LA tool: (unknown)

Satisfaction with course: (unknown)

Support, qualification: After getting to know the tool, he is interested in it. This increased his patience to wait for indicators to load fully.

Impact: The participant uses the tool to verify assumptions on the importance of certain learning materials. He needs time to draw conclusion on the data. He is optimistic that it could make a difference for his *awareness* and *changing his behaviors*, in order to work more efficiently (not necessarily only with regard to improving the course).

Course Description and User Profile

Similar to the other use cases, this course on the topic ‘basic mechanics and machine components’ was a combination of a weekly lecture plus exercise lectures, and several small exercise group meetings with supervision by tutors. Again, students had the opportunity to work on their own solutions, but it was not a mandatory learning activity. Also, up-to-date learning materials, such as exercise sheets, summaries, textbooks, literature, or old exam resources, were uploaded to the VLE on a weekly basis.

The TA of this course was responsible for the exercise course and had about five years of teaching experience. He reported diverse analytics experiences with spreadsheets and tools like MATLAB, but not related to LA (*experience: general experience with analytics*).

The optimal student behavior, as defined by him, would be as follows: students are encouraged to first read the chapter in the textbook, which is corresponding to the topic of the week's lecture. Afterwards they should visit the lecture. In the same week they should have a look at 1-2 problems in the exercise sheet and go to the exercise lecture to receive answers to their questions before they solve the problems independently within the small exercise groups one week later. The course instructor was particularly interested in the focus the students put during learning, demonstrated by their use of materials. In his experience, however, many students only collect the sample solutions and then master the exam only if they have the necessary skills anyway. But some students are working more continually. Those, who are actively participating in the exercise course, e.g., by asking questions, usually have a good chance to perform well in the exam. He based his experiences upon observations regarding the students' participation in face-to-face meetings and the results of university-wide evaluations, which helped to collect feedback from all students in a standardized format (*experience: students' behavior*). Furthermore, the TA was a person, who was willing to act upon these findings. For example, he reported that he learned from students' feedback that the usage of red and green colors for highlighting important differences during lectures was bad for color-blind people. So, he changed this in following lectures.

Impact Forecast

Due to the course description, the user's profile and his explicitly stated questions, we predicted that he would be particularly interested in observing the access to resources. It was quite obvious, since he told us upfront that he would like to observe which resources are accessed how often at what times. Also, indicators about exercise course participation and exam performance could have been interesting for him.

Pilot Phase Review

In this use case, the pilot phase during the semester failed because of a critical error – probably a performance related bug – during the first LA session by this user. He tried to open the tool after he had received our email, which stated that eLAT was available for usage. Then he closed the tool, because it took him to long to load the data, and used it again 10 weeks later, shortly before the interview. He argued that during that first session, it was not important to him to use the tool; otherwise he might have been willing to wait for it to load the data properly (*tool reliability: reported error kept him from using tool*).

In the interview, he stated (*surprise: little access to course information, experience: can be explain with changed file name*):

"*Okay. So, I think the data is in principle relatively interesting. I take care in creating and updating documents. And, if you can see whether and how the document is used, it brings some feedback and possibly a rating of whether it makes sense to keep on maintaining these documents. For example, I've just detected that course information that we put together at the beginning of the semester and that we update regarding the dates of the lecture, which may also change during the semester; that this course information file was not really accepted. First, I thought this. But then I noticed... that the situation is more difficult to analyze because we have changed the file name sometimes.*"[42]

This showed us his interest in specific data and some potential to increase the usability of the tool, which will be discussed further down. The interviewee was also quite interested in the students' accesses to exercise sheets, supporting notes, and old exams. Therefore, he liked the indicators related to access best. He noticed that the old exams had been accessed more than the other documents and explained further (*interest: access to documents*):

"*So far, this is actually the most important data for me: How often are documents accessed? Yes, if the tool would work better, then I would also use it during the semester or - maybe not I personally - but I would tell my student assistants, please, have a look. And how often were the documents downloaded? Have they really downloaded them the same day when we had uploaded them or only two minutes before the exercise ... onto the iPad or something? Then, to analyze how important it is that we upload the stuff on time.*"[43]

In general, he was interested in all the data, presented within eLAT, but he stated that he needed more time to analyze it before he would be able to draw conclusions on it (*way of using tool: needs more time for analysis*). As long as, the information is important to him, he would be willing to put some effort in the

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[42] Translated from: "Ok. Also ich finde die Daten prinzipiell schon relativ interessant. Man macht sich ja doch mit dem ein oder anderen Dokument relativ viel Mühe. Und wenn man dann mal sieht, ob und wie das Dokument genutzt wird, bringt einem das ja ein Feedback und eventuell eine Bewertung, ob es sinnvoll ist das eben weiter zu verfolgen, diese Dokumente zu pflegen. Da hab ich beispielsweise vorhin gesehen, dass Veranstaltungsinformationen, die wir am Anfang des Semesters zusammenstellen und aktualisieren in Bezug auf die Termine, die während des Semesters sich auch ändern können, ja, dass diese Veranstaltungsinformationen nicht wirklich angenommen wurden. Dachte ich erst. Aber dann ist mir aufgefallen, ich es gar nicht... dass es schwierig ist, es aufzuwerten, weil wir den Dateinamen irgendwann geändert haben.".

[43] Translated from: "Also insofern, das sind eigentlich spontan die wichtigsten Daten für mich: Wie oft werden die Dokumente überhaupt angefragt? Ja dann, wenn das Tool gut funktionieren würde, dann würde ich es auch während des Semesters nutzen und also – vielleicht nicht unbedingt ich persönlich – aber ich würde den Hiwis sagen, schaut mal nach bitte, wie wurden denn die Dokumente runtergeladen? Wurden die jetzt wirklich direkt an dem Tag, an dem wir sie hochgeladen haben, runtergeladen? Oder erst zwei Minuten vor der Übung... aufs iPad oder so? Um das dann mal zu analysieren und zu schauen, wie wichtig ist das denn überhaupt, dass wir die Sachen pünktlich hochladen.".

analysis or instruct student helpers to complete the tasks for him. He was not able to understand the indicator ‘activity behavior’, which required active settings of the user. After listening to an explanation, he reflected that the information was pointless for his particular purposes.

It was especially notable that he would like to improve his course regarding the efficiency of his document maintenance for students. If he would find out that he is putting too much effort in updating files, which are not used by the students, he would rather quit this unnecessary activity and put more effort in teaching activities, which are more helpful to students. In the interview, several issues about how to improve eLAT’s user interface were raised.

Improvement Suggestions

Even though most of the requested information regarding file access was supported by eLAT, some missing analytics options and usability issues could be detected during the user test. First of all, it was too difficult to answer the user’s essential question: “*How often have specific (groups of) resources been accessed?*” Especially, it should be easy to analyze the overall access on specific document folders regarding flexible time frames, which can be chosen by the user. Again it was mentioned that the time frame of the indicator ‘adaptivity’ (see section 6.5.2) should be extendible to contain the time span of the whole semester, not just 72 hours. A new indicator could also explicitly tackle the question, whether learning materials have been uploaded in sufficient time before the lectures.

Other suggestions were related to the improvement of interaction and analysis features. For example, this user asked for a zooming feature, too. Also, as pointed out in the ‘Pilot Phase Review’, file names might be changed during the semester. This might not be detected by an analytics system itself and different file names might be interpreted as different files even though they could be different versions. Hence, one file would appear as several files in the data visualizations. One way to deal with this is to track the renaming of files. Another way is to give the user a feature, which allows him to select different items, which belong together, and merge the related data during the analysis activity. Also, some filtering options should be revised, e.g., lists of file types, which can be selected, should only include those file types, which are known to the user. Otherwise, the file types list becomes too long and incomprehensible. The order of the documents, which can be selected by filtering options, should be presented in the same order they have in the course room of the VLE. Also, the filter-based configuration of different lines and bars of diagrams should be designed more carefully to avoid absurd correlations.

Within this user test, the personal filters, like ‘gender’ and ‘field of study’, were regarded less useful. Therefore, from this user’s perspective they could be removed or inserted further down in the list of all filtering options. The list of all filtering options should also be consistent for all indicators. Eventually, it became clear that – even though the teaching assistant liked the general structure of the prototype (dashboard and analysis view) – he additionally wished for embedded statistics, close to the actual learning materials. Furthermore, his questions regarding some indicators' calculation processes and wordings, such as the definitions of 'accessor' and 'access'[40], showed that these have to be renamed or explained carefully by context-sensitive help sections.

Discussion
Due to his little usage of eLAT, the user had the feeling that he had not yet analyzed the data enough to make conclusions. Still, he stated that his assumption about old exams being an important learning resource was verified. He was also sure that a tool, like eLAT, could make a difference. An interesting extract from the interview showed possible reactions of this user to his LA findings (Figure 43). We asked, if the tool could make a difference to his awareness and he answered:

> "*Yes, that could surely make a difference. So the best example ... or easiest for me now ... is then, related to some documents that are not accessed, yes, then I do not need to upload them either. If nobody cares, why should I be bothered?*"[44]

Thereupon, we asked him, if this would always be his conclusion for documents that have little access or if he could imagine searching for reasons. Then he reconsidered:

> „*Yes. That's a good question. This is probably connected to exam results. If 100% or 90% of the students regularly fail the exam and do not access important documents, then I would certainly put the focus on it, to look, why are they not doing that? But if the course itself is going well and the students do not access certain documents, well, then they obviously do not need them. Then the course will also work fine without it.*"[45]

His statement reveals several risks: The first conclusion that was drawn in this example could be wrong. Here are some questions that the user should ask himself before jumping to action: Could the document be beneficial for a small group of learners? Has the importance of the document been mentioned up front to the students? Are students planning to use the document later (e.g., oral exam

[44] Translated from: „Ja das könnte mit Sicherheit einen Unterschied machen. Also bestes Beispiel... oder für mich jetzt einfachstes... ist das dann bezogen auf manche Dokumente, wenn die nicht abgerufen werden, ja, dann brauch ich sie auch nicht hochladen. Wenn es keinen interessiert, warum soll ich mir die Mühe machen?".

[45] Translated from: „Ja. Das ist eine gute Frage. Das kommt wahrscheinlich darauf an wie jetzt generell die Ergebnisse sind. Wenn 100% oder regelmäßig 90% der Studenten durch die Klausur durchfallen und die wichtige Dokumente nicht abrufen, dann würde ich da sicherlich den Fokus drauf legen, um zu schauen, warum tun die das denn nicht? Aber wenn die Lehrveranstaltung an sich gut läuft und die Studenten gewisse Dokumente nicht abrufen, gut, dann brauchen Sie die offenbar nicht. Dann klappt es auch ohne.".

preparation with e-lectures)? Was the document not found because of a bad file system structure?

His reconsideration also shows that several factors should be included in the decision. Firstly, the type of learning material is important for the conclusion. If the teacher himself considered a file as important, he or she probably will not remove a document rashly. In the case above, the decision was made dependent on whether the course outcome is going well or badly. He refers to the exam results. It is therefore likely that the change would affect only the next semester. So, he makes the decision rather in a retrospective reflection (see, reflection-on-action, section 4.1.2).

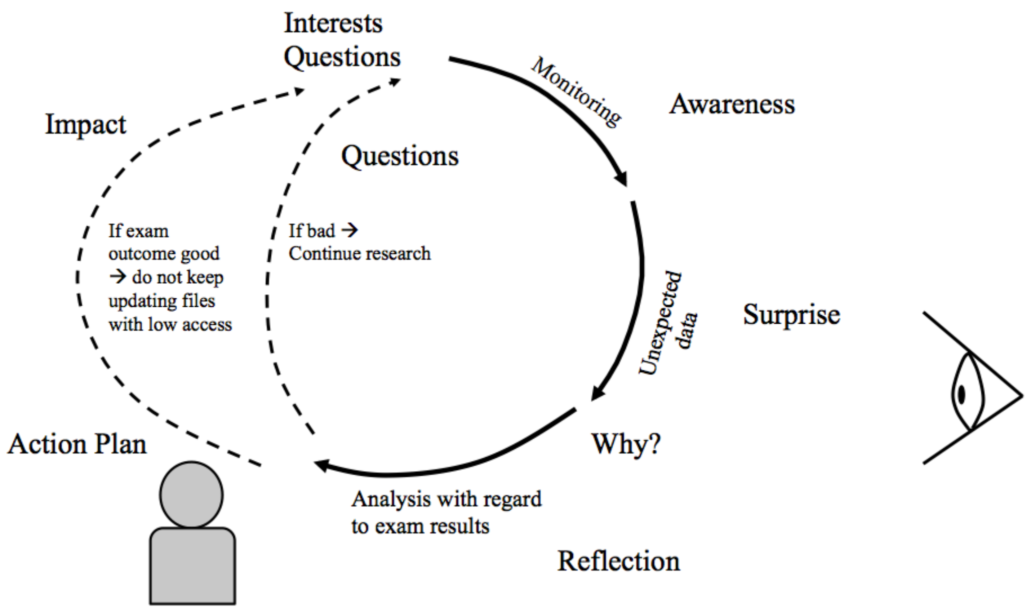

Figure 43. Expectation and reaction cycle of UC6.

His consideration regarding the exam results and the dependent reaction also shows something else: If 90-100% of the students fail the exam, then it is more likely that more is going wrong in the course than just the document access. Hopefully, an LA tool does not lead to wrong conclusion, like, that this is only due to the documents' design. In this case, other factors should also be investigated. However, it shows that correlations by a tool could potentially lead to misdiagnoses because other hidden factors. This could impact teaching and learning in a negative way. A future research question is: How should this potential risk be addressed through LA design?

7.4 Findings regarding the Research Questions

The participants accessed eLAT two times on average, i.e., once per month (see Table 14). Two participants used the tool spontaneously in the context of other teaching activities in L²P (UC1 and UC5). All others used it, when they had received our emails. In five cases, the long loading times of the visualizations demotivated the participants so that they used the system less than they would have actually liked to use it based on their interest (UC1-UC3, UC5, UC6). For this reason, we adapted the semi-structured interviews. We asked all participants to freely explore eLAT during the interviews while talking to the moderator (Think Aloud strategy). This additional system usage experience helped them to talk about and rate the system. Also, we were able to determine which reactions the tool usage caused during the interviews. The sections above summarize the main characteristics of the answers of each pilot user.

Table 14. Number of sessions with eLAT during the pilot phase.

Interview no.	UC1	UC2	UC3	UC4	UC5	UC6
#Sessions during pilot phase	4-5	1	2-3	2-3	3	1

During the coding process, which has been explained in section 7.1, we created a mind map of all the codes that we found, and we drew relations between these, in order to capture our hypotheses regarding the dependencies between them (Figure 44). The central category was the 'LA process cycle', which was varying in each use case (see Figure 38 to Figure 43). The LA process included certain subcategories, which emerged consistently. These subcategories were, e.g., 'assumptions', 'questions', 'surprise', 'sense-making, and 'action plan'. This was conforming to the theoretically deduced ARLA process model (see section 5.2.2).

We also found additional patterns: The use case discussions in the section above showed that the LA process stories of our users were diverse. The observed processes (see Figure 38-Figure 43) can be described as variations of the abstract model depicted in Figure 14 (section 5.2.2). We also found several core factors, which had influenced the different user stories, such as 'level of experience', 'level of surprise', 'level of involvement', 'level of trust', 'tool reliability', etc. (see section 5.2.3).

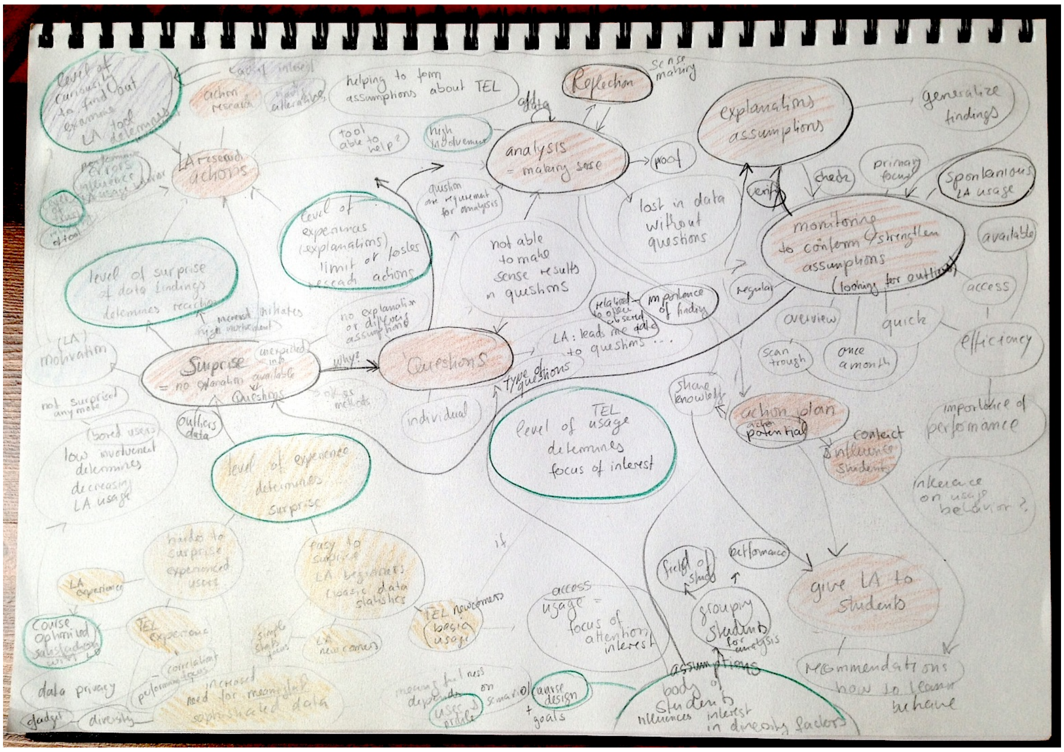

Figure 44. Photo of the mind map of central coding categories.

We included these factors into the ARLA process model. The abstracts of the use cases above give examples on how these factors have influenced concrete LA use cases. The next sections summarize the findings of the impact evaluation with regard to the LA objectives: ‘awareness’, ‘reflection’, and ‘action’.

7.4.1 Awareness

Awareness is a pre-condition for reflection. Furthermore, understanding the activities of people in ones context lays the ground for following activities (Dourish and Bellotti 1992). Awareness helps us deciding about our next steps, in order to reach certain goals. For instance, a car driver needs to know, if he or she is getting closer to the destination or if something is going wrong. We need to be aware about important information, which help us determining our next steps. Of course, we do not need to know every detail, but we need to have a good overview of the important things (Duval and Verbert 2012).

Therefore, this thesis studied the impact of eLAT on awareness and asked the question: *How should LA tools be designed so that teachers are aware of the students’ online behavior and diversity issues concerning students?*

In the context of the ‘car example’, it follows that LA designers need to provide information, which is important for LA users. This information needs to be quickly graspable within short LA sessions, as the usage of eLAT in the pilot phase showed. Especially, eLAT's monitoring view was designed for data inspection, in order to achieve awareness (see section 6.5.2). Most of our participants used eLAT about 10-15 minutes on monthly basis, and they mainly used the launchpad's monitoring view. Hence, this starting page of the LA tool should be designed for quick access. Visualizations, e.g., need to load in less than a minute. In order to reach this goal, they could be pre-calculated.

Users became aware about certain facts and tried to match them with their own knowledge. Monitoring the data was comparable to 'a search for outliers in data' or to 'verification of assumptions'. A teacher, e.g., might assume that students' dropout rates increase especially after the first week of a course because then they decide, which lectures they really want to put in their schedule. But not all students deregister from a course in this case. The number of deregistering students would certainly be a good indicator. The teacher could also have a look at statistics on student access to the VLE of the last two weeks. This way, the teacher might observe that usage is dropping and he or she would be 'aware' of this situation, but it might not be surprising. This teacher might also become 'aware' that one discussion post has an extraordinary high number of views and answers. This could surprise him or her and provoke further analysis. So, awareness might lead to analysis activities. An LA tool should allow for browsing different perspective on relevant data, without overloading the monitoring view to prevent that important information is overlooked.

In five of the use cases (all besides UC2), we found signs for awareness and assumption verification. In UC2, we observed ignorance, which can be seen as the opposite of awareness (see section 4.1.1). In all the use cases (all besides UC4), awareness facilitated by LA led to at least one surprise at some point during the monitoring activity.

With respect to 'awareness of students' behavior', the pilot phase revealed several deficits regarding eLAT's user interface. In all use cases, we noticed increased awareness regarding the indicators on usage of learning materials, which were located in the upper left corner. Four of the participants explicitly reported that this was most interesting to them. It was not intuitive to understand the grouping of the indicators into the four categories of widgets (see section 6.5.2). Nobody was interested in all groups. So, from users' perspectives, indicators with no or less interesting data took more space than interesting information. The participants asked for 'bigger visualizations', 'zoom features', and for 'personalizing the dashboard' (see 'improvement suggestions' of sections 7.3.1 to 7.3.6). Furthermore, information on students' behavior, which might have been interesting, was not directly found, or not well understood. Hence, personalization regarding the selection of content for the dashboard and arrangement of the data is important for the users.

We noticed interest in certain diversity issues, especially regarding the 'field of study' filter. Teachers assumed that there might be differences among students, who study courses with different study backgrounds. Due to their majors, they might have different previous knowledge or motivation regarding the topics of their course. The 'gender' filter was not important for teachers. One stated that he was mostly only curious to have a look at it. Others were not at all interested, probably because they wanted to avoid comparing males and females. Only one person (UC4) stated that it could be interesting to explicitly study gender differences, e.g., in order to examine how providing new slides, which are written in gender neutral language, is accepted by different groups of students with regard to numbers of access. The same teacher wanted to group students by their performance, e.g., 'students, who performed well on midterm exams', 'students, who are on the border of passing/failing', and 'students, who failed'. He guessed, it might be interesting to correlate this with other properties, like the access to certain materials or the participation in interactive tests or exercise courses. We did not ask, how the participants of our study felt about data on other diversity issues besides 'gender' and 'field of study', such as 'cultural differences' or 'disabilities'. Nonetheless, one teacher stated that he would be interested in differences regarding different study degrees, such as 'master/bachelor'.

The greatest obstacle with regard to diversity and performance filters was data privacy. We were not allowed to use too many different kinds of private data because they might reveal too much information about individual users. Of course, from an ethical point of view, it is good that we needed to make comprises regarding the usage of personal data. It needs to be handled carefully. Based on this situation, special techniques based on 'design by contract' for LA and data mining environments have been developed in the context of this thesis's work (see section 6.4.3).

The overall conclusion regarding the impact on awareness was that eLAT made the users mostly aware about usage of learning materials, but also supported awareness of students' online access behaviors and certain differences based on diversity filters. Additionally, our interviews gave insights into possible improvements of the design, which have been presented in the user stories' descriptions. However, if we want to achieve awareness regarding the whole learning process, we need more sophisticated indicators, which include additional data besides the one provided by VLEs, making more intelligent use of findings from the fields of EDM and IV.

7.4.2 Reflection

At first, all participants monitored the information presented by eLAT and explored their assumptions and prior experiences, in order to understand it. According to the definition of Boud, Keogh, and Walker (1985) this can be interpreted as a reflective activity. We could also observe occasions of surprise and inner discomfort. These situations led participants to ask: 'Why?' So, it initialized reflection and critical analysis activities (see reflection definition by Atkins and Murphy (1993) in section 4.1.2). Only in UC5, the TA did not trust eLAT's data calculations. Caused by this, he did not reflect on the data revelations, which actually had surprised him shortly before. So, instead of reflecting about possible conclusions, he tended to blame the tool (section 7.3.3).

Overall, it can be concluded that the LA tool had impact on reflection, as soon as it produced meaningful data and the values of the influencing factors were beneficial. Which data was meaningful was dependent on the user profile (e.g., beginner versus advanced user), the course design, the data, and the analytics performed with the data. Furthermore, the interview situation, the think-aloud method, and our questions might have influenced users to react in this way. We kind of fostered 'reflection-on-action' with the think-aloud method, which was necessary to make the process of reflection more explicit (see section 4.1.2). This is a limitation, which should be kept in mind regarding the outcomes of the evaluation.

So, *how should LA tools be designed so that teachers are encouraged to reflect on the quality of their teaching?* LA tools need to provide meaningful data. What is actually meaningful is individual in each use case, and therefore hard to predict. AR methodology provides a hint for this design challenge. Reflection begins with detecting problems and asking questions, while monitoring the data. For example, LA tools could make these 'questions' more prominent. In eLAT, these questions were only in the users' minds and teachers had to decide about how to answer them by choosing the right analytics metrics themselves. This process could be improved by letting the users choose 'questions' instead of 'indicators/metrics' and, hence, support them in matching these questions to indicators. Furthermore, they should choose their questions in the beginning of the LA cycle (see Figure 14, section 5.2).

7.4.3 Action Research

The last question is: *How should LA tools be designed so that teachers are inspired to explore and improve the quality of their teaching in terms of action research?* During this impact evaluation, we noted 'awareness', 'reflection', and the 'intention to act upon observed data'. eLAT helped to identify actions that could generate improvement, which is defined as an AR property by Hinchey (see section 4.2.2). These actions were, e.g., writing an email or contacting students in other ways. Therefore, LA tools should give direct access to 'actions' that teachers are likely to perform after analyzing the data, e.g., sending an email to students and attaching a specific indicator visualization status. This could increase the chance that they really act.

Besides UC4, we could not see, the intention to systematically study certain aspects, e.g., by trying to find answers to certain individual questions with self-selected methods. On the contrary, the behaviors or the participants were rather unsystematic. However, during the monitoring of LA visualizations several individual questions were raised by the teachers, which is a key property of AR (see section 4.2).

Trying to answer own questions helps to gain more knowledge about everyday situations. Berg (2001a) states:

> "*One could reasonably argue that all research requires action. After all, research itself is a type of action, and most research produces some sort of consequence (even apathy). With many types of research, the consequence is some sort of change or modification with the way something is done or understood. If our approach is metaphysical, the very act of asking questions and actively seeking answers can be viewed as a kind of intervention into a situation or problem, and will inevitably bring about changes in those individuals involved. Whether these individuals then choose to continue along the same paths as they had before the research was conducted or to change their course, means the new situation will either be different from before or remain essentially the same. In either event, the decision to change or not to change constitutes action or, more precisely, action or inaction.*" (p. 180f)

His view is that 'asking questions' is an 'action' itself, and 'seeking answers' is a kind of intervention. When taking this perspective, our findings show that LA has impact regarding AR, but there is still potential to increase this impact.

In this thesis, it is concluded that what was observed was rather 'reflection' than 'action'. AR is more intentional and more systematically planned. LA was used within the semester on a monthly basis, and also in the end for summative evaluation. During the semester, LA supports 'on-the-fly reflection', which can also be described as reflection-in-action, which occurs during an activity (see section 4.1.2).

A disadvantage could be that LA gives practitioners the feeling that they are doing AR (UC4), when they are actually just reflecting in a less systematic and intense way. But LA has a high potential to initiate continuous reflection activities, which could be called 'reflective teaching practices' and which in turn could lead to more systematic AR. So, teachers should additionally be qualified by training sessions, in order to transform 'on-the-fly reflection' into a more systematic methods analog to AR. This might increase their involvement.

In the context of supporting environments, it should be noted that Lockyer, Heathcote, and Dawson (2013) highlight the need for the field of LA to establish a contextual framework that helps teachers interpret the information that analytics provide. They suggest using learning design documentations, which present objectives and pedagogical plans, as a context for interpreting analytics data. It can be used both during a course in order to intervene (e.g., by emailing students) and after a course with the intention to redesign it. This idea actually, is similar to

EMAR the AR framework by McPherson and Nunes (2004), which was introduced in chapter 2.

AR has been called ‘participatory action research’, because it should involve all individuals in a study, i.e., it should involve teaching staff and students. Our advanced LA user (UC4) mentioned in the interview that he would like to show analysis results to his students. So far, most LA tools involve one person to interact with it and analyze the metrics. This could be improved by supporting several users – including the students – to collaboratively use such tools, e.g., by having shared views, posing questions, conducting analyses together, saving them, actively sharing the results with others, and interpreting them together.

All the findings mentioned above helped to inform the requirements collection and led to the creation of a final ARLA interface, which takes the role of an AR mentor, who provides information, but leaves important decisions to the user (A. L. Dyckhoff 2011; A. L. Dyckhoff, Lukarov, Muslim, et al. 2013).

7.5 Discussion and Conclusion

The collection and analysis of use cases led to the conclusion that eLAT facilitates especially LA beginners to reflect about their courses and students (see UC1, UC3, UC5, and UC6), unless they are clear opponents of LA (see UC2). An open question is, how more advanced users would use an LA tool. It is assumed that they need more sophisticated indicators to keep them interested. Unfortunately, those are the indicators, which are problematic with respect to data availability and data privacy. For example, performance data, such as grades, is often stored outside of VLEs and, if it is available, data privacy prohibits to process it. So, enhanced data collection methods, protective algorithms, and respective evaluation iterations are needed, in order solve these problems.

Besides the findings regarding awareness, reflection, and AR, this study observed certain factors, which might have influenced the success or failure of each ARLA process iteration (see also section 5.2.3). The different abstracts of UC1 to UC6 show how to briefly illustrate a user, his or her LA usage, and the impact, with the help of the influencing factors. These abstracts are easy to read. They support quicker detection of patterns in larger samples of use cases. Furthermore they can be used to demonstrate and explain impact to LA system developers. The influencing factors and their values can also be used for the creation of quantitative evaluation methods, e.g., in order to develop items for questionnaires, which estimate the levels of each factor for a user. Future studies should evaluate and extend this list of factors (see section 5.2.3).

The impact evaluation regarding eLAT was conducted with teachers of six TEL courses of RWTH Aachen. These courses, which used a central VLE provided by the university, were all typical for German lectures. But – as noted by Kerres et al. (2009) and Chatti (2011) – VLEs are not really 'learning platforms' instead they mainly serve for distribution of content and information, while communication and collaboration among students occurs elsewhere. This was probably the central reason, why the participants of the impact evaluation were mainly interested in indicators regarding access to certain resources and students' access behaviors.

A limitation of the evaluation described above is that the course selection did not match the diversity of courses in higher education. It needs to be acknowledged that there are other types of courses, such as, classical seminars or laboratories, thesis supervisions, but also massive open online courses. Future research should study how the ARLA model is suited for teaching models other than only blended learning lectures. Does it make sense to use LA in smaller courses with less than 100 students? The selection of courses for the pilot phase was limited to courses with many students (>100), due to data privacy concerns of RWTH's data protection officer. So, this question needs to be answered in future evaluation runs.

This overall chapter gave detailed insight into a qualitative study regarding the use of eLAT in higher educational settings, with the objective to learn about its impact on teachers' awareness, reflection and action. It described the methodological approach and showed findings in form of use cases and user stories. The analysis verified the ARLA process model and gave evidence for awareness, reflection, the potential for action, and related success factors.

eLAT proved to be widely suitable for the goals that most LA research strives for. The thorough documentation of this study will help future LA researchers to get to know how an LA tool was used and how it affected its users. However, more knowledge on the subject has to be gained by future research. It cannot be assumed that every LA tool has the same impact as other LA tools. Use cases are diverse, even if they have some similarities.

The suggestions, which were collected in this impact evaluation, were useful for redesigning eLAT's interface. Therefore, the following chapter presents the final ARLA concept and describes a concrete ARLA user interface, including, e.g., the most important requirements, guidelines for future developments, and recommendations for its integration in higher education.

8 ARLA MODEL AND ARCHITECTURE

The contents presented in the following sections are based on thorough theoretical and practical studies regarding the research topic ‘Action Research and Learning Analytics for Higher Education’. In the context of design-based research (see chapter 3), it introduces and reviews the final artifact of the overall research process. This artifact is the ARLA model. More precisely, it is a bundle consisting of requirements, user interface specifications, system architecture description, and guidelines. The outcomes of this research can be applied to the problem domain and, hence, should inform future projects and the design of ARLA systems.

8.1 Requirements Catalogue

The next sections structure and present the main requirements and an exemplary specification for development projects that aim at implementing ARLA concepts. The following discussion of the catalogue of requirements is a summary of the most important results of several development and evaluation iterations. It is divided into non-functional requirements and functional requirements.

8.1.1 Non-functional Requirements

The full list of non-functional requirements includes three more requirements than the initial list, stated in section 6.1. Additional to usability, usefulness, interoperability, extensibility, reusability, performance, and data privacy, it adds:

- Personalization
- Correctness
- Qualification and support provision

The most important non-functional requirements from a teacher’s perspective, and based on the experiences of this work, have been usability (ease of use), usefulness, personalization, performance, and qualification provision. As an external constraint data privacy was a substantial influencing factor because it limited the application of several indicators within real world scenarios.

Usability of the interface, meaningfulness of the data presented in it, and loading times of all kinds of interface elements have a great influence on how LA beginners perceive an LA system and decide about using it in upcoming course events. Good performance and efficiency is crucial because long waiting times can be interpreted as system errors. This can lead users to distrust in the reliability of indicator results and hinder reflective thinking.

However, the participants of the pilot phase in WS12/13 did not attach importance to ‘real-time data’. This might be due to the fact, that they only used the system on average once per month. Nevertheless, data should be current, i.e., present information about past activities up to the current day. However, it does not need to reflect the current hour; at least as long the respective use cases are similar to the blended learning scenarios, presented in section 7.3.

Findings of the impact evaluation led to adding the requirement ‘correctness’ to the final catalogue. LA tools shall work correct in the sense that teachers can rely on the completeness and timeliness of the underlying data, the adequateness of the visualizations, and the accuracy of the algorithms, which perform the indicator calculations.

Furthermore, the provision of qualification, e.g., by training courses or tutorials, and support, e.g., by context-sensitive help systems and support staff, are necessary, despite usability engineering.

8.1.2 Functional Requirements

In the following, the categorization of the catalogue of functional requirements is explained. The full list of requirements can also be found in APPENDIX A.

The overall list of requirements, which have been collected by this thesis’s work, has been structured into 15 categories:

1. Action Research Design
2. Analysis and Interpretation Support
3. Personalization
4. Help Documentation and Support
5. Tool Activation, First Use, and Learnability
6. Diversity, Clustering, and Filtering
7. Data Privacy
8. Correctness
9. Consistency
10. Collaboration and Communication
11. Integration and Interoperability
12. Openness, Extensibility, and Data Triangulation
13. Performance and Saving Time
14. Storage and Data Model
15. Question/Indicator Requests

The following sections describe the requirements of each category and reference them though *R_ID-value*, e.g., the very first requirement is *R_01_00*.

Action Research Design

Requirements in the 'Action Research Design' category are clearly dedicated to supporting AR, but other categories include requirements related to AR as well. These requirements can likewise inform the design of general LA systems with other target groups than teachers, such as students.

The ARLA system is supposed to take the role of an AR mentor, as recommended in Dyckhoff (2011). So, the main requirement is that it needs to include and support key AR tasks, such as formulating a question, developing a research plan and goals, systematically collecting data, analyzing the data, developing and implementing action plans, and recording the project in writing (*R_01_00*). Indicators should be clearly connected with the questions they are related to. Users have questions in mind, so they should choose 'questions' instead of 'indicators'. The system should support them in matching their questions to suitable indicators. If a teacher wants to view data, the first step should always be to choose a question from a catalogue, or formulate it, and then browse through and choose suitable indicators (*R_01_04*).

The system should also assist groups of users to jointly formulate research questions. This requirement is based on Berg's (2001a) statement that it is "*the task of the investigator is to assist individuals in the stakeholding group to jointly formulate research question(s) [...]*" (p. 181f). So, all users should have the same configuration, and changes of who changed what when need to be traceable (*R_01_01*). Additional requirements with regard to collaboration and communication are discussed below in the section about the category 'Collaboration and Communication'.

The system needs to provide selections of research questions that are actually answerable. This requirement is based on Berg's (2001a) second part of the same statement: *"[It is] the task of the investigator is to assist [...] in formulating questions that are actually answerable*" (p. 181f). A dedicated LA team of the university should be responsible for the provision of these answerable questions in a question catalogue (*R_01_02*). Further details on the tasks of the LA team are given in 'Help Documentation and Support'.

The system shall allow its users to select and create indicators for their own questions (*R_02_00*), which have been previously formulated by the teachers themselves. Each question, which can be chosen in the system, needs to be associated with a goal, so this goal can be used to inform students about the objectives of the study, as data privacy regulations demand (see BDSG). As soon as a question is added for analysis, students should be able to view these goals in an information page regarding the LA project (*R_01_03* and *R_07_02*).

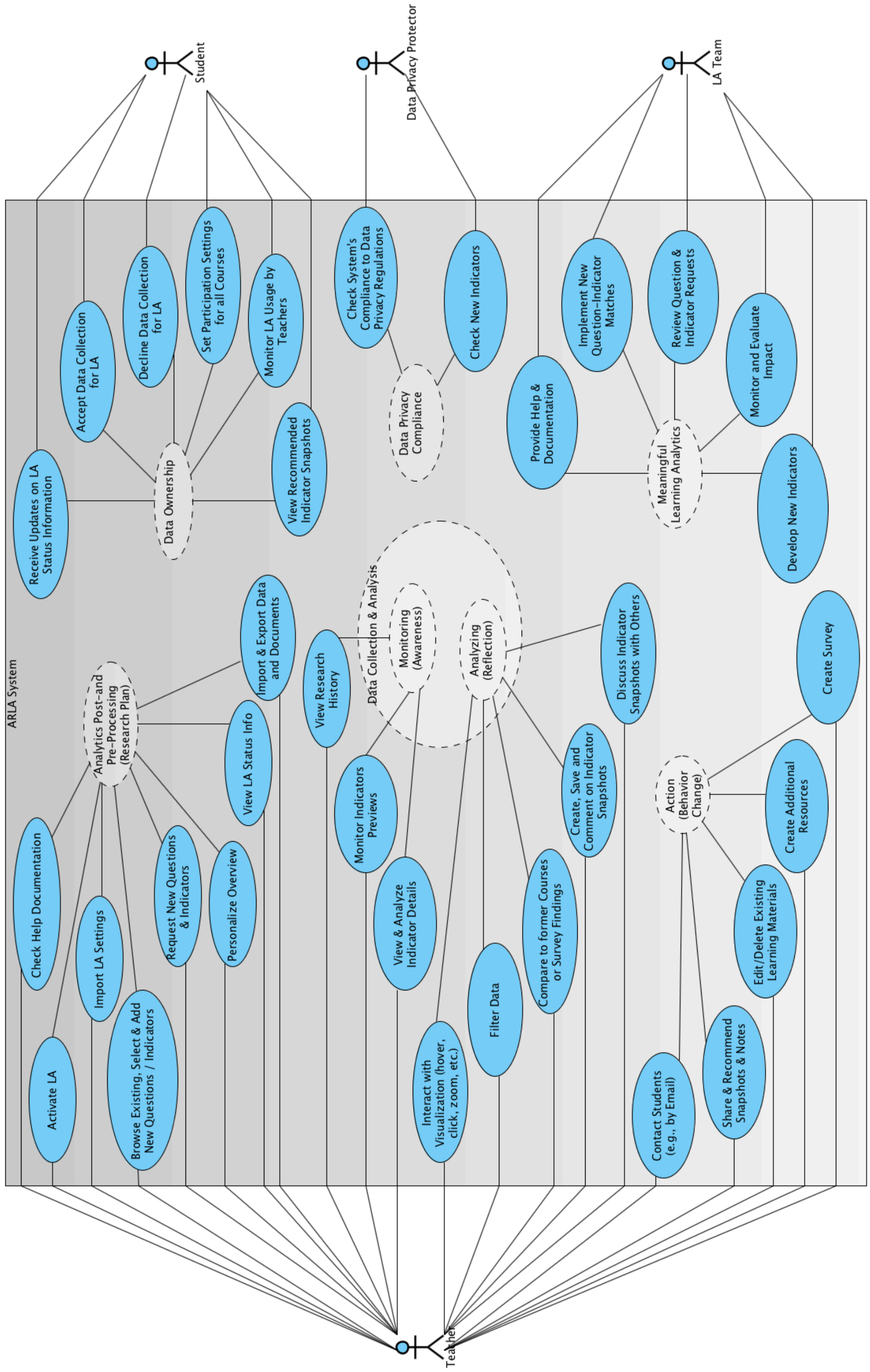

Figure 45. Use case diagram of the ARLA system.

Furthermore, the system could provide features to collect and structure typical data with regard to AR, i.e., all kinds of documents and artifacts, journals, field notes, interview recordings, survey results, and all kinds of audio or video tapes, or photos (*R_01_05*). This could, e.g., be easily achieved by integrating wikis and document libraries with LA tools.

The ARLA system itself shall give quick access to VLE features, which support 'actions' that teachers are likely to perform after analyzing the data, e.g., sending an email to students and attaching a specific indicator visualization status (*R_01_06*). In order to design for redesign (AR cycle), it shall be possible to import LA configurations, such as selections of questions and respective filters, from past courses (*R_01_7*). The ARLA tool shall provide the possibility to compare the data of each question to the results of former semesters (*R_01_08*). Figure 45 shows the most important use cases of all stakeholders. These were the basis for extracting the requirements above and below.

Analysis and Interpretation Support
The system shall provide customizable overviews and possibilities to drill-down into data (launchpad approach) (*R_02_00*). The first page provides an overview and it is understood as a 'monitoring view' (e.g., see eLAT, section 6.5.2). It provides an individual selection of questions and their respective indicator visualizations, so that users can quickly grasp current information. The selection of individual interests is represented by a clearly visible option to 'add own questions' to the monitoring page. Drilling down into data becomes possible with 'analysis views'. The feature for adding a new research question to the monitoring view shall be also visible in the analysis view (*R_02_01*). Access to analysis features shall be clearly visible in all available monitoring views[46]. Users need to recognize the possibility to change filters/parameters for each question also on the monitoring view (*R_02_02*). The analysis views of indicators shall present data in form of visualizations, or combinations of visualizations and data tables, or in combination with natural language. All these representations need thorough evaluation (*R_02_03*). Visualizations should be simple, i.e., beginners need to understand them without much cognitive effort. Nevertheless, the system should provide documentation for all visualizations (*R_02_06*). To be precise, the system should provide detailed help, including a tutorial on how to systematically use LA for AR (*R_04_08*).

For an engaging analysis experience, visualizations should be interactive, in order to give more information and be more useful (*R_02_07*), e.g.:

- They should be resizable and provide a zoom feature (*R_02_08*).
- Data points should provide tooltips, when hovering over them (*R_02_09*).
- Users could be enabled to add and map remarks to image areas (*R_02_11*).

[46] Note that there can be more than one view for the monitoring view, so users can choose with one suits their needs best (*R_02_04*, *R_02_05* and *R_03_00*).

- Clicks on document titles could link to the respective document or show previews (*R_02_10*).

Personalization
Each user should have his or her preferred view regarding the layout of the starting page, e.g., as a dashboard or list view with larger visualizations (*R_03_00*). Teachers shall be able to select questions from lists of prepared questions, and add these to their central monitoring view of the particular course (*R_03_01*).

The system should provide browsing features for exploring all the available questions and indicators based on keywords (*R_03_02*). Furthermore, the list of all available questions could provide filtering mechanisms based on natural language processing, as soon as there are too many items available (*R_03_03*). Questions and indicators should include metadata, such as a 'categories' or 'tags', in order to structure and filter them. For example, there could be the categories: usage, students behavior, performance, and collaboration (*R_03_04*), as suggested by Bültmann (2011). Such metadata will help a user to search and filter for certain questions or indicators. But they should rather not be used to design a static monitoring view as described in section 6.5.2.

The starting page of the system shall be customizable in the sense that all questions can be arranged, resized, deleted, and added as determined by the user of the LA system (*R_03_05*). Users should be able to choose, which granularity indicator visualizations on the starting page they would like to have, e.g., daily, weekly, monthly overviews (*R_03_06*). Furthermore, the layout of the system should fit on different screen sizes (e.g., mobile or large desktop screen) (*R_03_07*).

Help Documentation and Support
Users can receive assistance on multiple levels, such as: system usability, human support, and system documentation.

The system should speak the users' language, with words, phrases and concepts familiar to the user, rather than system-oriented terms. Nielsen (1993) additionally recommends following real-world conventions, making information appear in a natural and logical order (*R_04_00*). For instance, the naming of the LA tool as a feature within a VLE shall not evoke wrong expectations, e.g., 'statistics' is a problematic wording because users can interpret it in different ways (*R_04_01)*. Actually, although 'learning analytics' is not well known, it seems to be quite suitable because it does not lead users to misunderstandings of the functionality of the tool. No expectations are better than wrong expectations. This was found in user tests in November 2013, when ‘statistics’ was used on a trial basis instead of ‘learning analytics’ to name the tool. Another helpful system feature is the clear labeling of visualizations (*R_04_04)*, e.g., by providing the date and time of when a diagram was last updated (*R_04_05)*.

A dedicated LA team shall maintain the system and offer training sessions (*R_04_02)*. The LA team also reviews users' requests for new questions and indicators, supports these users by suggesting existing alternatives, or implementing the new ideas (*R_04_03)*. Figure 45 also shows the main tasks of the LA team.

Figure 46. Structured indicator documentation. Source, Lukarov (2013).

The goals of a perfectly usable system cannot always be met (Nielsen 1993). An LA system should provide informative help because the interpretation of visualization can lead to diverse conclusions. One participant of the pilot phase with eLAT suggested (UC5), e.g., a short documentation or video tutorial (both graspable in 3 minutes) for introducing the tool's main structure and the purpose of single features, such as indicators (*R_04_07)*. Optimally, the system should provide detailed help. This overall help documentation should be printable as a handbook. According to Nielsen (1993), it should be easy to search, focused on the user's task, list concrete steps to be carried out, and not be too large (*R_04_08), "since many users rarely use the manual before they absolutely have to"* (p. 149). The requirements *R_04_09 to R_04_12* give more details on essential content of LA manuals. In particular, each question-indicator-mapping should have a separate description. Lukarov (2013) recommends a structured indicator documentation (see Figure 46) for describing the use cases, underlying data and calculations, how to interpret the indicator, example questions, and limitations. This also applies for structured question documentations (*R_04_10)*.

Such indicator documentations are similar to patterns. They could be helpful for LA researchers as well, in order to understand and compare their indicator findings with those of others.

Tool Activation, First Use, and Learnability

The requirements of this category are concerned with using the LA system for the first time, what to do in the beginning of each semester, and how to design it to make it learnable for LA beginners.

First of all, there is the question of who starts the LA study how and when? It could, e.g., be activated by default. Then the system should inform the staff as soon as the new tool is activated; e.g., when creating a new course room. If it is deactivated by default, managers of a course need to be able to activate the LA tool, e.g., within the settings page of a course room (*R_05_08)*. In the process of activating the LA system, it should provide general LA goals that are suitable for most courses by default. Teachers need to check or edit and then accept these goals (*R_05_05)*. Or they should specify their own goals or choose from default goals. These goals are needed for transparency reasons with regard to data privacy regulations; e.g., in order to automatically inform students about the objectives of collecting their data (*R_05_07)*. They will be presented to students, as soon as the data collection is supposed to start together with a request for accepting the data collection (*R_05_05)*. As soon as the data collection is activated in a course, all current and future students, who registered for the particular course, will be notified about the projects goals and dates of data collection (e.g., via pop-up window), when entering the course room. They will be asked to accept or decline the data collection before their data is stored in the LA database (*R_05_04)* (see Figure 45). During the tool activation process, the user, who activates the system, should be asked to set start and end dates of the data collection. There should be a default setting, like 'first day of semester' until 'first day of following semester'. The start and end date should be editable later on, as long as they have not yet passed. Students shall be informed about all LA study details (*R_05_06)*.

When the system has been initialized, the first page of the system should provide two or three example questions with corresponding data visualization, in order to give LA beginners a sense of which functionality the tool provides (*R_05_01)*. The feature for adding questions to this monitoring view needs to be clearly visible, in order to motivate users to actively personalize their user experience (*R_05_00)* (see also section 'Personalization'). Examples of analytics, i.e., questions with indicators that are provided in the initial starting page in the beginning of a semester, should provide answers to questions that are meaningful for most users (*R_05_02)*. Therefore, the LA providers need to have a good understanding about their target group. They should observe the usage of the LA tool on an ongoing basis.

Labels of visualizations and the naming of filtering functions need to be clear for LA beginners. Visualizations should contain sufficient and simple labels to support a first time user to interpret them in the intended way. Most beginners should be able to guess the outcomes of using certain filtering option right before testing them (*R_05_03)*.

Diversity, Clustering, and Filtering
According to Schulmeister (2004b), the tool should present the diversity of students to the user. The system should provide diversity filters, such as 'field of study', 'bachelor/master', and 'gender'. The pilot phase, discussed in chapter 7, showed that ‘gender’ was least preferred for analysis. An ordering by most preferred to least preferred filters is recommended. Indicators need to allow users to adjust values of filters, such as limiting the visualized data with respect to selected time frames or groups of students with certain properties, e.g., 'computer science' field of study (*R_06_00)*. The tool should also make it possible to group students into certain clusters (e.g., by field of study, performance, or by all students that have never accessed the course room page) and relate these groups to other data, such as usage patterns (*R_06_01)*. This is a feature that especially advanced users wish for. If users have applied some filters, the indicators' visualizations should present clearly, which filters have been used on the data (*R_06_02)*.

Data Privacy
The BDSG influences this group of requirements (see section 5.2.3). All systems, implemented within German course settings must be conforming to data privacy regulations (*R_07_00)*. Students need to have the opportunity to accept or decline that their own data is used for LA in a specified course (opt-in and opt-out). They should be asked for every course that uses LA, unless they configured general acceptance or decline in their profile settings (*R_07_01)*. Students shall be informed about the goals and form (e.g., dates, research questions, and types of data) of each particular LA study in the beginning of each semester. These goals and an overall study description should be always accessible, e.g., on a related information page regarding each course. Especially, it needs to be present during the data collection acceptance procedure (*R_07_02)*. For transparency reasons, students should have an overview of all the selected questions and corresponding data (*R_07_08)*. If a student declines with regard to the usage of his/her own personal data, this data is not going to be stored anymore or it is deleted from the database. If he or she accepts the data collection, the data is stored in the analytics database from that moment on, unless he/she refuses to participate later during the course (*R_07_03)*.

Teachers should have an overview about the numbers of students, who accepted or declined to participate in the LA study. This information could, e.g., be shown on a general LA information page regarding the particular course (*R_07_04)*. The system should hide data results, if less than a certain number of students, e.g., five students, with a particular set of properties are among the results of the indicator calculations. This number needs to be verified with the data privacy officers of the respective institution (*R_07_05)*. New indicators need to be checked with regard to data protection before they are provided within the user interface (*R_07_09)*. All visualizations should to by anonym, or at least pseudomized, depending on the context of the study (*R_07_06)*. All data shall be stored in a pseudomized way. The pseudonymization needs to be repeatable, in order to successively add data to student profiles. For eLAT, e.g., a hash of the username was created (*R_07_07)* (section 6.4.3).

eLAT stores user data in a pseudomized form and publishes only pre-defined, anonymous visualizations. But during the research for this thesis, also an alternative possibility was explored: Design by contract with respect to academic analytics (Hackelöer 2011) (section 6.4.3).

Correctness
A correct system is a critical requirement for creating trust, which in turn is essential for creating impact. The system needs to prevent errors and provide emergency exits, especially during the first usage sessions, because malfunctions can prevent users from using the system in the future (*R_08_00)*. Error messages should be expressed in the users language, precisely indicate the problem, and constructively suggest a solution (*R_08_06)*. Furthermore, in order to prevent misinterpretations, the system should provide normalized visualizations, and present current data[47] in relation to the whole group of registered students (*R_08_01)*. Additionally, it should prevent users to make configuration mistakes, e.g., the system should warn managers, if filter selections are irregular (*R_08_07)*. The system should indicate missing data and fragmentary data sources (*R_08_02)*.

Consistency
According to Nielsen (1993), all usable systems need to follow platform conventions. So, this should also be true for LA tools, which are integrated in an overall learning environment. Users should not have to wonder whether different words, situations, or actions mean the same thing (*R_09_00)*.

In the evaluation of eLAT's Launchpad UI (chapter 7), we found, e.g., that the filter options should be more consistent for each indicator, e.g., the time frame filter should always provide the possibility to chose every time frame within the past semester (*R_09_01)*. Another example was that the interface should keep the orderings of document filters analogue to the order of folders and files in the related VLE (*R_09_02)*.

[47] Data should optimally be updated by extracting current data from the connected VLEs during 01:00-04:00 a.m. every 24 hours, and not less than once a week (R_08_04).

Collaboration and Communication

AR is not about one person, who evaluates a course, and university courses are often conducted by a group of people, like a professor, teaching assistants, and student helpers. Hence, ARLA systems should be designed for involving more than one person into the analysis process. Teachers and their assistants need a shared view on the system, in order to jointly answer AR questions; e.g., they could have the same configuration per course. All configurations regarding the content of questions and analytics in one course should be the same for all managers of the course, so they can interpret them together and coordinate actions. They also could share their notes (*R_10_00)*. Therefore, the system should provide the possibility to share questions, data, and notes with others, e.g., with student helpers or even with learners (*R_10_01)*. In this case, changes within the configurations need to be traceable for the users, i.e., they shall have an option to see changes made by themselves and others (*R_10_02)*. This way, they can better understand, why their view was altered, based on changes conducted by others. Furthermore, it should be possible to save visualizations, e.g., as separate pages. These saved indicator state pages (snapshots) should be sharable with others. So, several users can have a look at them (*R_10_03)*. A saved indicator snapshot could provide possibilities to communicate about it within the same page and link it with other data (*R_10_04)*, similar to wiki features. This way it could also be referenced in emails to students.

Integration and Interoperability

The system needs to be available to the user during teaching activities. So, the system should be capable of being integrated in a course of a VLE (*R_11_00)*. Cooper (2013) highlights the importance of making the transfer of data to analytical tools easy. He did a survey on the current state of data exchange between multiple software systems. The system's data model should be prepared for including all relevant data of standard VLEs (*R_11_01)*. It should be possible to integrate outcomes of single indicator request that have been calculated by the LA backend into a VLE, e.g., each indicator could have its own web page. This way, indicators can be provided as apps within app-based systems (*R_11_02)*. In line with this requirement, the system should support single sign-on procedures (*R_11_03)*. Each question/indicator should have a unique identifier, in order to link to it for quick access during teaching activities within a VLE (*R_11_05)*. Each state of an indicator, which is represented by a set of filtering values and the resulting visualization, should be savable for later access, if the user chooses a related 'save this data for later access' button. This saved snapshot should have a print layout (*R_11_06)*. A saved indicator state should be accessible via a distinct link, so users can come back easily or reference to it, when discussing with others (*R_11_07)*.

The underlying database needs to have programming interfaces for importing and exporting externally collected data (*R_11_04)*. Furthermore, integrate outcomes of central, standardized questionnaires into the system and let users choose if they want to visualize the results in their starting pages (*R_11_08)*. During all interviews, participants and moderators sought to confirm observed phenomena by comparing indicator results. Hence, credibility was increased, if the same information appeared in all indicators. This could even more increase, if further data could be included, such as results from questionnaires.

Indicators regarding specific modules of a course room (e.g. assignments) should be integrable into that particular module in the sense that managers can access these indicators directly, when working with a module, such as editing learning materials (*R_11_09)*. Hence, the system should provide APIs for all elements, in order to be closely integrable into any VLE (*R_11_10)*.

Openness, Extensibility, and Data Triangulation
Several findings showed: LA system architectures need to be open and extendable in the sense that they allow for easy implementation of new indicators ideas (*R_12_00)*. Average users, who do not want to develop indicators themselves, should have opportunities for specifying and requesting new ideas for indicators, if they do not find suitable ones for answering their questions in the systems (*R_12_01)*. Constant need for new indicators, based on diverse usage scenarios and questions, call for an easily extendable data model, which can incorporate new types of data. For example, eLAT provides *UserExtensions* and *AssetExtensions*, in order to extend the predefined options (*R_12_08)*. It would be nice if users could develop their own questions and indicators and provide them for others. But because of data privacy protection, the LA development team and a data protection officer need to be included in all stages of the development process of new indicators (*R_12_02)*.

Furthermore, this work suggests that the LA system should not narrow the view to certain data (e.g., by only focusing on usage data); although some users are satisfied with only one aspect (*R_12_07)*. Observing advanced users has shown that an LA system should provide the opportunity to triangulate data of different sources with regard to the same question (e.g., combine usage statistics with survey questions). It should also be possible to compare quantitative results of indicators with results from surveys within the LA system (e.g., by integrating survey apps into the starting page) (*R_12_04)*. The system should provide the option to add manually collected data (e.g., attendance numbers or exam results, in order to compare increases and decreases in file usage with in class attendance) to the database (*R_12_05)* and an export feature for the data of each indicator (*R_12_03)*. This will support advanced users to continue research on question, which are not supported by the system.

Performance and Saving Time
Performance had been an influencing factor during the impact evaluation (see chapter 7) because teachers and students have little extra time within their daily routines and they do not want to spend this time by waiting for LA results, especially if they are not sure, if it pays of.

The conclusion is that the monitoring view, including the visualizations on it, optimally needs to have loading times less than a minute. In order to reach this goal, it is advisable to pre-calculate questions/indicators and cache the respective visualizations (*R_13_00)*. Furthermore, users need to be informed about the duration of waiting times. The system should estimate the duration for an indicator calculation and inform the users, who sent the particular request, about what is going on (*R_13_01)*. It should also continue processing an indicator request, even if the user begins a new task. This way, the system allows the user, who sent an indicator calculation request, to work on other tasks during the waiting time. When finishing a report, the system should inform the user about this (*R_13_02)*, so he or she will pay attention to the results.

However, not only the quick loading of indicators saves time; e.g., good default settings are essential. All data visualization of questions, which have been added onto the monitoring view, should be based on real data of the respective courses. This saves time for users, who only want to click once and observe several metrics in one overview. Visualizations may be pre-calculated to make access to the monitoring views more efficient (*R_13_08)*. At first use, the system should provide default selections of filtering items, which make sense for most use cases, e.g., all filters should be selected by default (*R_13_03)*. The system should provide options to 'select all items', 'deselect all items', or 'select all items of a type' with regard to checkbox lists with several items (*R_13_04)*. For instance, it could be helpful for beginners to be able to select all questions from the catalogue of all available questions at once, get to know them in the context of their own data, and then delete those from the monitoring view, which have no relevance for the course (*R_13_05)*. Additionally, the system could provide a feature to get regular updates on the current states of LA by notification features (*R_13_06)*.

Storage and Data Model

As a result of the semi-structured interviews, the possibility to filter data was identified as a substantial requirement. However, when implementing the filtering options in prototype B, we did not yet entirely meet our goal of providing operations with good performance, which are necessary for a smooth user experience. One reason for this was the structure of the database, which had been created in early development iterations and, in its current form, had been designed according to a pattern used for operational databases rather than data warehouses. Hence, we needed to implemented on-the-fly generation of lookup tables, containing pre-calculated intermediate results, to increase the efficiency of filtering. A thorough redesign of the database scheme with data warehouse principles in mind is required to address this issue in greater detail.

The system should store all necessary data in a suitable data warehouse so that it delivers excellent query performance, even for complex analytic queries (*R_13_07)*. It needs to take into account established e-learning standards for its data model (see section 5.1.4). The data model should be independent of certain educational software (*R_14_01)* and it should include all relevant objects that need to be observed in a blended learning scenario, e.g., see eLAT data model (*R_14_00)*. The implementation of the user interface should be independent from storing and calculating the data (*R_14_02)*, in order to adjust the views to the respective environment, in which the LA system integrates. The system should store the raw data results of indicators calculations, so different graphic web interfaces can interpret them, and results of different reports can be compared (*R_14_03)*.

Question/Indicator Requests

The amount of available indicators and support tools for finding fitting items are critical factors for the success of a LA system. A user, who does not find the report in the system, which is relevant to him or her, will probably not use the system again. It is therefore necessary to cover the questions and concerns of target users well. In this work, several preliminary user studies tried to find out which indicators are considered to be useful by many users. However, even with a large set of available indicators new issues, which are not yet supported, can occur. In this case there are two possibilities: Firstly, the individual person, who requires a specific evaluation, could contact members of the LA team and define a new indicator together with them. On the other hand, the system could be designed in an open way, so that the teachers themselves, for example, could create their own database queries, use statistical tools and data mining, and choose appropriate visualizations. But the latter possibility poses a major security deficit in relation to data protection. Therefore, in the context of eLAT the decision was made that new indicators have to be developed in collaboration with users, tested individually regarding data protection, and authorized before deployment. However, as part of the diploma thesis of Hackelöer (2011) the possibility of design by contract regarding analytics was discussed and exemplary implemented within a general EDM framework (section 6.4.3). This kind of implementation opens new possibilities for advanced users.

eLAT User Interface B (Launchpad), which was used as the basis for extensive evaluations, did not implement all indicators, which had been defined and evaluated in the previously conducted iterations. This was a matter of time and also due to the fact that not all the data needed was available at the time of implementation; e.g., it lacked of data corresponding to session information and durations or more detailed metadata about students. Furthermore, using performance/grade-related data was an issue, which led to severe discussions about data privacy.

About 20 indicators have been implemented for eLAT; six of which have been presented above. The indicators have let to differing opinions during evaluations. Their usefulness rating was very much dependent on the underlying didactical scenarios.

Beginners might be satisfied with simple usage statistics, but advanced teachers want to analyze the data with respect to correlations and the generation of recommendations (A. L. Dyckhoff, Lukarov, Muslim, et al. 2013). For example, they wish for statements such as:

- Students who are active in the VLE and have passed an average number of exercises, mostly also have a good test results.
- Students who have passed many exercises and have little overall activity in the VLE have mostly failed the exam.
- Students, who are registered in field of study XY, usually have rather bad test results.
- Courses with homework that will be corrected, often lead to regular and increased activity in the VLE.

On the basis of such rules, the next step would be to generate specific recommendations. The objectives are to facilitate decision-support and interventions that motivate students to improve their behavior and learning outcomes. Students may, for example, receive recommendations on specific learning materials, which they have not accessed. Teachers could be asked to provide certain groups of students some assistance. Furthermore, good students could be asked to share their knowledge with weaker students.

In the context of this study, it was investigated within a diploma thesis which data mining techniques are adequate for the purpose of generating recommendations for teachers (Lisson 2011). Lisson compared three data mining techniques, namely linear regression, general association rule mining, and class association mining. In addition, a Recommendation System for Teachers (ReST) was prototypically implemented. Its results can be used by different systems - including eLAT - via web services. The rules generated by ReST have so far only been evaluated by one course supervisor. Before recommendation systems can be integrated in concrete contexts in LA tools by default, still more extensive studies are required.

The results of indicator discussions with different interview participants supported our hypothesis that teachers should be enabled to explore data individually; arranging their own sets of indicators per course, to facilitate improvement of teaching. However, as stated above, it follows that there must be a large amount of indicators from which the users can select exactly those indicators, which fit their scenario. Because of this, the previously stated requirement 'Openness, Extensibility, and Data Triangulation' of a LA system is essential for its sustainability. A growing set of indicators should be well structured and easily searchable, so that every user can find what he or she is looking for.

This work resulted in a large pool of question/indicators descriptions and classifications. Example question/indicator classifications have been published in (A. L. Dyckhoff 2011; A. L. Dyckhoff, Lukarov, Muslim, et al. 2013; Bültmann 2011).

8.2 ARLA User Interface for the next L²P Version

Based on the findings of the impact evaluation presented in chapter 7, a final version of a high fidelity prototypes was designed and evaluated with user tests. This prototype of interface C (Question-based Launchpad) has been described in section 6.5.3. Its evaluation in November 2013 demonstrated the potential for further fine-tuning, especially, in the context of L²P. It needs to be noted that it was tested together with a new design for RWTH Aachen's app-based learning platform (L²P). This context led to more product-specific requirements, compared to the catalogue above, and also laid the focus on the new design. So, LA was only one of several topics within the user tests. The following paragraphs describe a possible solution for implementing the requirements catalogue listed above.

The ARLA launchpad should be a module of a course room, which can be activated or deactivated by managers, analogue to other L²P components, such as the optional exercise course (Stalljohann and Schroeder 2010; A. Dyckhoff, Rohde, and Stalljohann 2008). The standard view of the LA monitoring view is a customizable dashboard. However, users can choose also other views, such as for example the typical L²P document library look-and-feel, only with preview visualizations (e.g., similar to the video component). By default, there should be three questions in the monitoring view that represent the interests of many users. These should also show the possibility to correlate data in one of the indicators. Furthermore, the standard view shall include the 'add question/indicator' placeholder. Clicking on this 'add' button opens an assistant for 'adding a question/indicator to the monitoring view'. This feature should also be available in the ribbon bar, consistent to the overall L²P design, which is based on SharePoint 2013.[48] LA use cases, which are included in the ribbon bar, are presented in Figure 45, e.g., 'browse questions/indicators', 'import data', and 'contact students by email'.

Data is collected by a dedicated SharePoint feature, which is activated together with the ARLA launchpad integration. This feature collects data of all activated course room components, including even the LA component.[49] Hence, every existing and new L²P component should have a data collection concept, which is included in the data collection feature, whenever a new component is installed. Data collection does not start until a course room manager sets the start and end date and specifies goals of LA. This should be done during the LA activation process and it should be possible to change settings of the LA system in the L²P course room settings page.

When data collection is started, the L²P data is transferred daily into an ARLA data warehouse, where it is stored for at least one semester (up to the life time of a

[48] The ribbon bar is a context-sensitive menu (known from MS Office products) that gathers and provides all possible user interactions for a respective module.

[49] The data collection also collects data about the usage of LA, in order to be able to evaluate its impact also by usage numbers of certain items, or in order get ideas for new questions/indicators.

course room). The data is checked and pre-processed, in order to achieve correct analysis reports within seconds. These reports are basically data tables (e.g., regarding eLAT in form of JSON[50]), which can be interpreted by question/indicator apps. During the data transfer, only data of course participants, who accepted the data collection, should be included in a pseudonymized way in the XML files (see section 6.4.4). Nevertheless, the data transfer between L²P and the ARLA database needs to be secure. Furthermore, the system needs to check data of users, who declined, and delete their private data on a daily basis. All participants (including managers and tutors) should receive an email notification, when the data collection is started, and if possibly also a popup window, when using L²P. The popup presents study details and users need to be able to accept or decline the data collection. If they have set a general 'LA opt-in' for all courses in their personal settings, they only receive a notification about the goals of a particular LA study and the time span when LA is going to be used for a respective course.

A question/indicator app should consist of a widget view, with a question-related title in natural language, for the dashboard and a detailed analysis view, as a separate web page within the L²P course room design. Hence, wherever it is useful, an L²P module can reference the analysis view of every app; e.g., some users wished for integrating usage statistics into the learning materials section of L²P, in order to access it directly from there. The design of question/indicator apps needs to be consistent and fulfill the requirements stated in APPENDIX A. For better performance, such an app could be designed for also saving the results, date, and time of the latest report request; e.g., together with (thumbnail) previews of diagrams, notes, snapshots, and discussions.

For L²P course managers, i.e., teachers, the meaningfulness of an indicator very much depends on which L²P components are used in a course. Course managers that only distribute announcements and learning materials are likely to focus their interest on questions/indicators with regard to usage data. Teachers that also adopt interactive scenarios with, e.g., e-tests, assignments, and grade book modules, are more likely to show an interest in correlations with performance data of students. Nevertheless, all users should be able to see all available questions – not only those that are answerable in their scenario – because this could also lead them to change their learning designs; e.g., they could decide to use an online 'exercise course' module and a 'grade book' in following semesters.

8.3 System Architecture

The ARLA system needs to be modular, in order to facilitate seamless integration into VLEs, as described exemplary in the sections above. Figure 47 shows how

[50] JavaScript Object Notation (JSON) is a format for transmitting data objects between a server and a web application.

different courses include LA modules, such as LA course dashboards and apps, which can be also included in other webpages.

The backend with its database and calculation engine needs to provide web services and APIs. The code base and the data model should be easily extendable and open for new data types. Especially, it should be possible to import data of diverse VLEs; e.g., data from PLEs, social media platforms, and mobile data. Manual data input and qualitative data, such as student feedback in natural language, can be included. This data would need to be analyzed semi-automatically, or with methods of natural language processing.

There should be a data privacy layer. This should at least check how many users of a specific/predefined property (e.g., gender, field of study, nationality, etc.) have registered for a course. A decision has to be made whether to allow or deny analysis of the data. It should accept data analysis based on the number of students with that particular property, e.g., at least five students. Alternatively, there could be a design-by-contract framework for LA and EDM, as an enhanced version of the one explained before. This means that other contracts need to be checked also; e.g., who send a particular request could have an influence on the final decision if analysis results may be delivered to a user (section 6.4.3).

Based on the requirements in the catalogue (APPENDIX A), a data warehouse (with data marts/data cubes for each course/question) is recommended because it can store and process large amounts of multidimensional data, which should be accessible for users in a flexible manner. Furthermore, it can handle data from different sources (Figure 47).

The LA server (or server cluster) needs to be prepared for multiple, parallel requests by many course rooms at the same time. Client-based calculations are not recommended because of data privacy concerns (section 6.4.3). Therefore, the data privacy layer should secure the data exchange between systems.

Visualizations should be generated separately by different LA web applications, or mobile apps. The design of these applications should conform to the requirements in section 8.1.2.

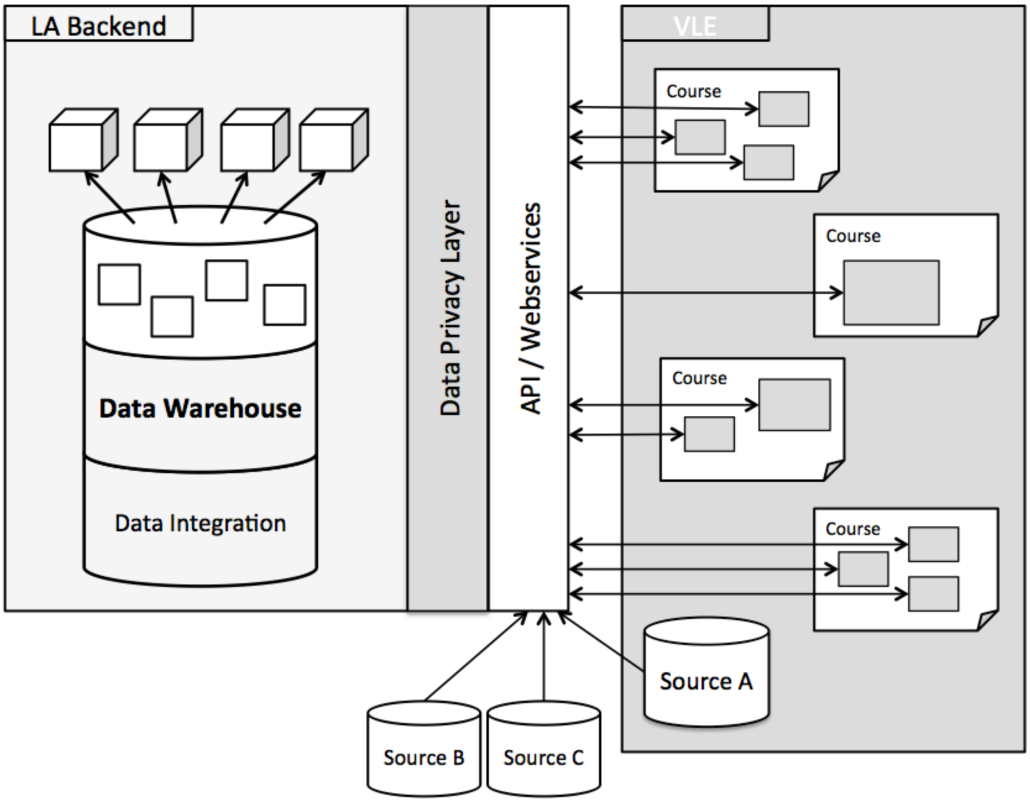

Figure 47. The ARLA system architecture.

8.4 Guidelines for Learning Analytics Application in Higher Education

This section lists guidelines, which are related to user interface design, and continues with recommendations for the application of an ARLA system in higher education. The number of guidelines was intentionally kept small, in order to focus on important principles.

As stated by Nielsen (1993), user interface guidelines list „*well-known principles for user interface design which should be followed in the development project*" (p. 91). The following interface guidelines are a summary of the most important 'product-specific guidelines' related to the ARLA model, but they are applicable to all user interfaces regarding LA tools.

ARLA user interfaces should fulfill Nielsen's (1993) 10 Heuristics and Few's (2006) information dashboard design principles. Particularly the following rules should be adhered to:

- Consistency: Be consistent (also with environment).
- Design for LA beginners and advanced users: Design a launchpad.
- Design for joy-of-use: Make LA optically pleasant, effective and efficient.

- Simplicity: Avoid fancy visualization.
- Engage the user: Let the user interact, reflect, and act.
- Help: Guide reflection processes with good documentation and support.

The most important UI guideline in the context of this work is:

- Lead to AR: Design for question and action.

The following recommendations on the application of the ARLA model in higher education are based on the findings of practical implementations in pilot studies. They have been structured into five categories.

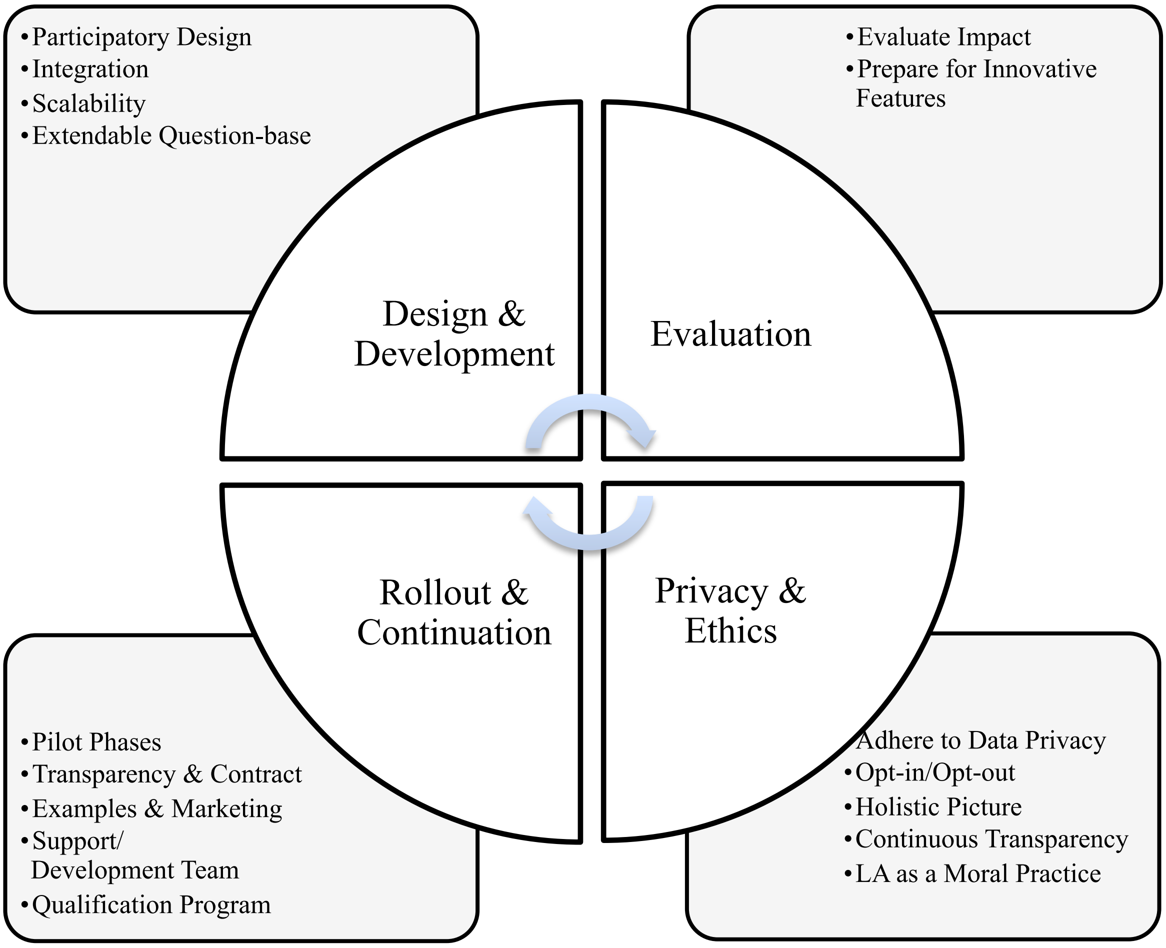

Figure 48. Guidelines of LA application in higher education.

Design and Development

- Participatory design: Involve teachers and students and stay in contact with them.
- Integration: Embed LA in the university's VLE and combine with other LA or survey tools.
- Scalability: Design technically for institution-wide implementation.
- Extendable question-base: Start out with a small set, and let it grow based on participants' feedback.

Evaluation

- Evaluate impact: Continue on gathering data about the usefulness for your institution and share knowledge with others.
- Prepare for innovative features: Analyze, which indicators are meaningful to whom and use this knowledge, e.g., to recommend questions/indicators pairs for certain courses.

Privacy and Ethics

- Adhere to data privacy: Take care of pseudonymous data storage and anonym visualizations.
- Opt-in/Opt-out: Let users choose to opt-out per course.
- Provide a holistic picture of learning: Show a broad spectrum of learning activities of the students' full experience.
- Continuous transparency: Give students insight into how their data is used, and continuous access to the information of each LA study.
- LA as a moral practice: Act responsible, if the data shows problematic issues.

Rollout and Continuation

- Start out with pilot phases before university-wide usage of LA, and use the experiences for collecting for specific requirements for the scenarios at hand.
- Transparency and contract: Communicate the scope and role of LA deployments clearly and formulate a contract with students on how LA will be used.
- Examples and marketing: Provide use cases for demonstrating benefit and usage in diverse scenarios, and advertise the benefits from all stakeholders' perspectives.
- Support/development team: Provide help, documentation, maintain the system, and continue to iteratively enhance and improve it. A dedicated LA team should support users' requests.
- Qualification program: Provide trainings with regard to AR methodology.

It should be noted that neither eLAT nor ARLA are implemented, yet, for university-wide usage. Therefore, the recommendations above need to be evaluated further, but they can guide further steps in this direction.

9 CONCLUSION

From today's perspectives of teachers, LA are replaceable; e.g., by maintaining close contact with students and regularly asking for feedback. However, in large classes, it is often too time-consuming to consider all learners' perspectives and it can easily happen that teachers focus on a particular group of students. While only interacting with these students, they might neglect the needs of other groups, without being aware of it. Several participants of our evaluations mentioned that they like talking to students to receive feedback. The question is: Are these students' answers and opinions really representative for the whole course? Since most teachers agreed that good students were active and bad students were rather inactive, they probable talked to active and therefore good students and extracted only their learning experiences. The danger is that they tend to generalize from these few discussion; not only for the particular course, but for all future courses. That might be a reason, why experienced teachers feel like their courses have been optimized. Although each setting is a new situation since there are new students.

LA could represent a tool, which helps in keeping a more objective overview. Starting from a surprising observation with the help of LA, it would be possible to gain new insights. This does not mean that other methods should be replaced. On the contrary, teachers should continue collecting and analyzing qualitative feedback and be open for diverse opportunities to get to know their students. LA should rather be a tool to initiate further studies and situated learning about teaching and learning.

In this study, the impact of LA was considered in conjunction with AR. This innovative view revealed new facets about the LA research domain. By embedding LA in AR methodology, LA promises to be a powerful tool. However, there is still a bumpy research road ahead of us. And so far, the costs of analytics – especially, with regard to 'data' and 'privacy' – often seem to be higher than their benefits.

In many typical higher educational scenarios, LA serves mainly as a tool for teachers that facilitates them to check whether everything is running as expected. As long as these scenarios are similar to the use cases, described in section 7.3, LA would be a tool, which only confirms expectations and, accordingly, its impact on teaching will be hard to detect. LA has the potential to initiate teachers to take action, when providing meaningful data, and it very much depends on the teacher's skills, what he or she makes of the newly gained knowledge. Therefore, we also need to qualify staff for effective usage of LA.

Apart from rather traditional courses, LA can have higher impact in exploratory TEL scenarios (e.g. MOOCs). If the amount of learning materials and possibilities to collaborate is too large to read, watch, and learn everything, then LA could make a difference. It could facilitate observing diverse groups of students, paving their individual learning paths.

From a teachers perspective, in particular, data outliers in the negative sense would be interesting to watch, i.e., the documents that are not accessed, or the students, who do never show up in statistics. Are these the documents that students do not need? Or is it too hard to find them? Do these students need help? And how can we support them? If teachers could find the reasons, intervene, evaluate their interventions, and improve learning by making teaching in courses with many students a more personal experience, this would be a great use of LA.

Yet, we still find classical lectures as essential and frequently applied teaching methods in higher educations. But nowadays, students have the possibility to move beyond the local offerings of universities and participate in courses of other institutions as well. How will this situation change higher education? How will the way we learn look like in the future?

In this context the following two quotes fit quite well:

> „*The best way to predict the future is to invent it*." (Alan Kay)

and

> „*It takes almost as much creativity to understand a good idea, as to have it in the first place*." (Alan Kay, in a Talk in San Jose 2002).

This thesis represents only one step along the way of understanding the idea 'learning analytics', and to make it useful. It is important that LA adjusts itself to learning, not the other way around. Clow expresses this chance as follows:

> „*All metrics carry a danger that the system will optimise for the metric, rather than what is actually valued. This danger is not new – Kolb argued emphatically that 'learning is best conceived as a process, not in terms of outcomes' ([11] p. 26) – but learning analytics makes it more pressing*." (Clow 2012)

In this dissertation, several research questions have been posed (see chapter 1), which had not been sufficiently answered by related works (see chapter 2). These were answered by following design-based research principles (see chapter 3).

Chapter 4 provided the terminological basis for answering the research questions. Chapter 5 tackled the questions regarding the dimensions of LA when put in relation to AR. Its contribution to the field of LA is the ARLA reference model, which may support LA projects to classify own developments and analyze initial situations. The description of a project with the ARLA reference model also helps to expose areas of conflict. These might be differences in intentions of stakeholders, data privacy regulations, or unsolved technical challenges. This work tackled several LA challenges and describes possible solutions, e.g., how to deal with data privacy and how to achieve meaningful LA. The third research question, on how LA dashboards might influence typical blended learning university lectures, was answered by implementing diverse LA prototypes and evaluating these in practices (see chapter 6). Chapter 7, presented the outcomes of a qualitative impact evaluation. The main finding was that LA can facilitate awareness, reflection, and has at least the potential to lead into AR.

Which indicators are meaningful to whom? The answer to this research question first was supposed to help LA developers creating LA dashboard templates for different courses. During the study, it turned out that every observed use case was different. So, the decision was made that teachers themselves should decide, what is meaningful to them. Personalization and question-based approaches are also important, when considering AR methodology. A catalogue of about 130 requirements and specifications for ARLA systems evolved from the experiences of this work (see chapter 8). This catalogue can support the development of future LA systems. It may also be used to check existing tools and improve them, where necessary.

Furthermore, the influencing factors of LA usage can be used to conduct more, larger, and longitudinal evaluations, in order to measure the impact of LA quantitatively or in different contexts on the long run. Also further qualitative studies will improve knowledge about the LA processes.

Future research should strive for open LA, in order to sketch a more holistic picture of learners and their learning. So far, data is only drawn from a few systems, focused on central VLEs. But learners do not only learn with these tools. They create their own personal learning environments and much of their learning also happens ‘offline’. The access of student-generated mobile data is a promising approach of collecting more complete information on learning processes and factors (Wagner 2013). Maybe students are willing to tell their teachers, how they learn, on a regular basis? Mobile technology and ever present possibilities of ‘apps’ could make it easy for students to semi-automatically record their learning behaviors, provide new forms of feedback, and even gain individual benefits, e.g., by observing and reflecting on their own learning behaviors.

Such open LA calls for open data models and open implementations. These need to be designed, integrated in learning environments, and tested. For instance, the Society for Learning Analytics Research (SoLAR) aims at creating an integrated and modularized platform for open LA (Siemens et al. 2011), e.g., they require standards for improving extensibility of open platforms.

Another practical challenge will remain data privacy. The solutions described in this work are feasible to implement, but we do not know if and how people will make effective use of them in practice. Example questions are: Will enough students opt-in LA studies, so that teachers can observe their data? What are the social implications of this? What are the students' perspectives on LA? Additionally, the conflict between the needs of advanced LA users and data privacy remains. Siemens stated:

> "*The next generation of tools must be designed to serve a dual purpose: context-sensitive help and guidance for non-technical users and an accessible technical layer that allows more advanced users to interact directly with data and to tweak and adjust analysis models*." (Siemens 2012, p. 6)

So, how can we allow advanced users to create their own analytics and derive more meaningful information, while preserving privacy of students? Do data privacy regulations need to change eventually? I personally have the wish that I – as a data producer – own all my data traces and am able to decide whom I give access to which parts of it for which purposes.

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APPENDIX A

The following requirements catalogue is also available as an Excel-file with additional information on respective sources of each requirement, and with priorities rating. Please contact the LA team of CiL of RWTH Aachen University.

ID	Category	LA Requirements Description
01_00	Action Research Design / Task-based	The ARLA system shall include and support key action research tasks, such as formulating a question, developing a research plan (goals), systematically collecting data, analyzing the data, developing and implementing action plans, and recording the project in writing.
01_01	Action Research Design / Question-based Analytics	The system, which takes the role of an action research mentor, shall assist groups of users to jointly formulate research questions. This requirement is based on Berg's (2001) statement that it is "the task of the investigator is to assist individuals in the stakeholding group to jointly formulate research question(s) [...]" (p. 182). So, all users have the same configuration, and changes need to be traceable (who changed what when?).
01_02	Action Research Design / Question-based Analytics	The system shall provide selections of research questions that are answerable. This requirement is based on Berg's (2001) second part of the same statement (see 01_02) that it is "the task of the investigator is to assist [...] in formulating questions that are actually answerable" (Berg, 2001, p. 182). A dedicated LA team of the university, which provides answerable questions in a question catalogue, shall support the selection process of indicators for questions, which are formulated by teachers.
01_03	Action Research Design / Question-based Analytics	Each question, which can be chosen in the system, shall be associated with a goal, so this goal can be used to inform students about the goals of the study. So, if a question is added for analysis, students will be able to view the respective goal in an information page regarding the LA studies.
01_04	Action Research Design / Question-based Analytics	Clearly connect indicators with the related questions they tackle. Let users choose 'questions' instead of 'indicators'. Hence, support them in matching their questions to indicators. If a teacher wants to view data, the first step should always be to choose a question from a catalogue or formulated it, and then see or choose suitable indicators.

01_05	Action Research Design / Qualitative Data	The system shall provide features to collect and structure typical data with regard to action research, i.e., all kinds of documents and artifacts (document library with notes), journals, field notes, interview recordings, survey results, and all kinds of audio or video tapes, or photos.
01_06	Action Research Design / Action Initialization / Integration	The ARLA system itself shall give quick access to VLE features, which support 'actions' that teachers are likely to perform after analyzing the data, e.g., sending an email to students and attaching a specific indicator visualization status.
01_07	Action Research Design / Cycles	In order to design for redesign (action research cycle), it shall be possible to import LA settings/configurations (like questions and parameter-selections) from other courses.
01_08	Action Research Design / Cycles	The ARLA tool shall provide the possibility to compare the data of each question to the results of former semesters.
02_00	Analysis and Interpretation Support / Launchpad Interaction	The system shall provide customizable overviews and possibilities to drill-down into data (launchpad approach). The overview is the starting page and it is understood as the monitoring view (e.g., see eLAT). It provides an individual selection of questions and indicator visualizations, so that the user can quickly grasp current information. The selection of individual interests is represented by a clearly visible option to add own questions to the monitoring page. Drilling down into data becomes possible with an analysis view for each question.
02_01	Analysis and Interpretation Support / Easy Access	The feature for adding a new research question to the pool of own questions (= monitoring view) shall be also visible during the process of analyzing data.
02_02	Analysis and Interpretation Support / Easy Access	Access to analysis features shall be clearly visible in all the system's monitoring views. Users need to recognize the possibility to change filters/parameters for each question on the starting page (= monitoring view).
02_03	Analysis and Interpretation Support / Diverse Perspectives	The detailed views of indicators shall present data in form of visualizations, or combinations of visualizations & data tables, or in combination with natural language (as in the case of recommendations). All these representations need to be evaluated, i.e., they need to be understandable for the respective target group.

02_04	Analysis and Interpretation Support / Monitoring Views	The system shall allow for browsing different perspectives/views on the relevant data, without overloading the monitoring view to prevent that important information is overlooked.
02_05	Analysis and Interpretation Support / Easy Access	There should be a view of the starting page, which directly includes the analysis views for each questions, i.e., in this view filtering mechanisms shall be directly accessible from the starting page. Users can decide themselves, if they want to have this view as their default view or another one.
02_06	Analysis and Interpretation Support / Simplicity	Visualizations shall be simple, i.e., beginners need to understand them without much cognitive effort. Nevertheless, the system shall provide documentation for all visualizations.
02_07	Analysis and Interpretation Support / Interaction	For an engaging analysis experience, visualizations shall be interactive, in order to give more information and be more useful (e.g., overview, zoom, on-demand details, relations, extracts).
02_08	Analysis and Interpretation Support / Personalization	Visualizations shall be resizable or provide a zoom feature. They should provide more details on demand.
02_09	Analysis and Interpretation Support / Interaction	Visualizations shall be interactive in the sense that data points provide tooltips, when hovering over them with the mousepointer.
02_10	Analysis and Interpretation Support / Interaction	Visualizations shall be interactive in the sense that clicks on document titles link to the respective document.
02_11	Analysis and Interpretation Support / Interaction	Visualizations shall be interactive in the sense that user can add and map remarks/notes to previously selected image areas.
02_12	Analysis and Interpretation Support / Dynamic Visualization	It would be nice to have dynamic visualizations of how data developed over time (e.g., little movies like gapminder).

03_00	Personalization	Each manager can have a preferred view regarding the layout of the starting page, e.g., as dashboard or list view.
03_01	Personalization	Managers shall be able to select preferred questions from a list of all available questions and add these to the central monitoring (overview) page of the course.
03_02	Personalization / Browsing and Finding	The system shall provide browsing features for exploring all the available questions/indicators based on keywords, e.g., in order to find similar questions.
03_03	Personalization / Browsing and Finding	The list of all available questions shall provide filtering mechanisms based on natural language processing, as soon as there are more than 50 questions available.
03_04	Personalization / Browsing and Finding	Questions/Indicators shall have metadata, such as a 'categories' or 'tags', which they belong to. For example, there could be the categories: Usage, Students behavior, Performance, and Collaboration. Such metadata will help users to search and filter for certain questions/indicators.
03_05	Personalization	The starting page of the system shall be configurable in the sense that all questions can be arranged, resized, deleted, and added as determined by the managers of the system.
03_06	Personalization	Let users choose, which granularity indicator visualizations on the starting page should have (daily, weekly, monthly).
03_07	Personalization	The layout of the system shall be responsive (scalable) for fitting on different screen sizes (e.g, mobile vs. large desktop screen).
04_00	Help Documentation and Support / Wording	The system should speak the users' language, with words, phrases and concepts familiar to the user, rather than system-oriented terms. Follow real-world conventions, making information appear in a natural and logical order.

04_01	Help Documentation and Support / Wording	The naming of the LA tool as a feature within a VLE shall not evoke wrong expectations, e.g., 'statistics' is a problematic wording because users can interpret it in different ways. Actually, although 'learning analytics' is not well known, it seemed to be quite suitable because it does not lead users to misunderstand the functionality of the tool.
04_02	Help Documentation and Support / LA Team	The system shall be maintained by a dedicated LA support team. This LA team should also offer training sessions.
04_03	Help Documentation and Support / LA Team	A dedicated LA team shall review user requests for new questions/indicators, support the users by suggesting alternatives, or implementing the new ideas.
04_04	Help Documentation and Support / Labels	The axes of all visualizations shall be clearly labeled.
04_05	Help Documentation and Support / Labels	Each visualization shall provide the date and time of when it was last updated.
04_06	Help Documentation and Support / Labels	Whenever data visualizations show data related to time spans, users shall be able to include course dates into these visualizations.
04_07	Help Documentation and Support	The system shall provide a one page documentation or video tutorial (both graspable in 3 min) that introduce its main structure and features.
04_08	Help Documentation and Support	The system should provide detailed help, including a tutorial and how to systematically use LA for action research. This overall help documentation shall be printable as an overall LA handbook. It should be easy to search, focused on the user's task, list concrete steps to be carried out, and not be too large.

04_09	Help Documentation and Support	The help documentation shall be context-sensitive, i.e., when a users clicks on a help option, he/she will receive help on the currently used LA feature.
04_10	Help Documentation and Support	Each indicator, which is available in the system shall have detailed descriptions of the underlying data (without disclosure of private data), calculations, how to interpret it, exemplary use cases about how they have been proven to be meaningful for which problem in a specific course, and limitations.
04_11	Help Documentation and Support	The system should provide a glossary for terms, which are important for data interpretation, e.g., 'access' and 'accessor'.
04_12	Help Documentation and Support	The system should provide 1-minute video tutorials for each question and indicator that explain how to use them.
05_00	Tool Activation, First Use, and Learnability	The feature for adding questions to the starting page shall be clearly visible within the monitoring view, in order to motivate users to personalize their user experience.
05_01	Tool Activation, First Use, and Learnability	When the system is initialized, the starting page of the system shall provide 2-3 questions with corresponding data visualization, in order to give LA beginners a sense of what features the tool provides.
05_02	Tool Activation, First Use, and Learnability	Examples of analytics (questions with indicators) that are provided in the initial starting page in the beginning of a semester shall provide answers to questions that are meaningful for at least 90% of the target group.
05_03	Tool Activation, First Use, and Learnability	Labels of visualizations and the naming of filtering shall be understandable. Each visualization shall contain sufficient, simple labels to support a first time user to interpret them in the intended way. An LA beginner needs to interpret the labels of each visualization in the way they were intended to be interpreted. Filtering features need to be clear, i.e., beginners should be able to predict the outcomes of using certain filtering option before testing them.

05_04	Tool Activation, First Use, and Learnability	As soon as the data collection is activated in a course, all current and future students, who registered for the particular course, will be notified about the projects goals and dates of data collection (e.g., via pop-up window), when entering the course room. They will be asked to accept or decline the data collection before their data is stored in the LA database.
05_05	Tool Activation, First Use, and Learnability	In the process of activating the LA system, it provides general learning analytics goals that are suitable for most courses by default. So, teachers only need to accept them in most cases. These goals will be presented to students, as soon as the data collection is supposed to start (together with a request for accepting the data collection).
05_06	Tool Activation, First Use, and Learnability	During the tool activation process, the user, who activates the system, shall be asked to set start and end dates. There shall be the default setting 'first day of semester' until 'first day of following semester'. The start date can be edited later on as long as it has not yet passed. The end date can be edited as long as it has not yet passed. Students shall be informed about details like this in an LA study information page.
05_07	Tool Activation, First Use, and Learnability	In the process of activating the learning analytics tool, managers should specify their own goals or choose from default goals, in order to automatically inform students about it.
05_08	Tool Activation, First Use, and Learnability	The system should inform staff by email as soon as the new tool is activated (e.g., when creating a course room). Furthermore, updates within LA could be connected with notification systems in the respective VLE. If it is deactivated by default, managers of a course need to be able to activate the learning analytics tool within the settings page of a course room.
06_00	Diversity, Clustering and Filtering	The tool should present the diversity of students to the user. The system shall provide diversity filters, such as 'field of study', 'bachelor/master', and 'gender', ordering them by most preferred to least preferred. Indicators allow user to adjust filter values, such as limiting the visualized data with respect to selected time frames or groups of students with certain properties, e.g., 'computer science' field of study.
06_01	Diversity, Clustering and Filtering	The tool shall make it possible to group students into certain clusters (e.g., by field of study, performance, or by all students that have never accessed the course room page) and relate these groups to other data, such as usage patterns.
06_02	Diversity, Clustering and Filtering	If there are filtering features, the indicators' visualizations shall present clearly (e.g., in legends), which filters have been selected on it.

07_00	Data Privacy	The system shall be conforming to data privacy regulations.
07_01	Data Privacy	Students shall have the opportunity to accept/decline that their own data is used for learning analytics in a specified course (Opt-in and -out). They should be asked for every course that uses LA, unless they configured general acceptance or decline in their profile settings.
07_02	Data Privacy	Students shall be informed about the goals and form (types of data) of each particular learning analytics study (course) in the beginning of each semester. These goals and a LA study description are always accessible on a related LA information page regarding each course and during the data collection acceptance procedure.
07_03	Data Privacy	If a students declines with regard to the usage of his/her own personal data, his/her data is deleted from the database. If he or she accepts the data collection, the data is stored in the analytics database from that moment on, unless he/she refuses to participate later during the course. This means that a feature to decline with regard to data collection needs to be available all the time, for the time the study is active.
07_04	Data Privacy	Managers shall have an overview about the numbers of students, who accepted or declined to participate in the learning analytics study. But not their names! This info could, e.g., be shown on a general LA information page regarding the particular course.
07_05	Data Privacy	The system shall hide data results, if less than a certain number, e.g., five, students with a particular set of properties are among the results of the indicator calculations. This number needs to be verified with data privacy officers.
07_06	Data Privacy	All visualizations need to by anonym or at least pseudomized, dependent on the context of the study and data privacy officer decisions.
07_07	Data Privacy	All data shall be stored in a pseudomized way (ideally anonymized, which prevents making logical connection between certain students and the collected data). The pseudonymization needs to be repeatable, in order to successively add data to student profiles. For eLAT, e.g., a hash with regard to the username was created.

07_08	Data Privacy	For transparency reasons, students shall be allowed to have an overview of all the selected questions and corresponding data. They do not need to be able to manipulate it.
07_09	Data Privacy	New indicators shall be checked with regard to data protection before they are provided within the user interface.
08_00	Correctness	The system shall prevent errors and provide emergency exits, especially during the first usage sessions, because these incidents prevent users from using the system in the future.
08_01	Correctness	The system should provide normalized visualizations, present data in relation to the whole group of registered students.
08_02	Correctness	The system shall point to (warn in case of) missing data and fragmentary data sources.
08_03	Correctness	The system shall track the renaming of files/different versions.
08_04	Correctness	Data should optimally be updated by extracting current data from the connected VLEs during 01:00-04:00 a.m. every 24 hours, but not less than once a week.
08_05	Correctness	Indicators shall only show elements of the course room, which are relevant for the interpretation (e.g., avoid counting clicks on layout elements of the VLE).
08_06	Correctness	The system shall provide error messages that clearly state what is wrong and suggest what to do next from the perspective of the user. Error messages should be expressed in plain language (no codes), precisely indicate the problem, and constructively suggest a solution.

08_07	Correctness	The system shall warn managers (e.g., to 'check filter settings again'), if filter selections are somehow mixed (false).
09_00	Consistency	The system shall follow platform conventions. Users should not have to wonder whether different words, situations, or actions mean the same thing.
09_01	Consistency	The filter options shall be consistent for each indicator, e.g., the time frame filter should always provide the possibility to chose every time frame within the past semester.
09_02	Consistency	The system shall keep the orderings analogue to the order of items/files in the course room.
10_00	Collaboration and Communication	Design for involving more than one person into the analysis process. Teachers and their assistants need a shared view on the system, in order to jointly answer action research question. They need to use the same configuration file. All configurations regarding the content of questions/analytics in one course shall be the same for all managers of the course (shared domain), so they can collaborate with regard to interpretation and action. The also need to share their notes.
10_01	Collaboration and Communication	The system shall provide the possibility to share questions, data, and notes with others, e.g., with students or student helpers.
10_02	Collaboration and Communication	Changes within the configurations shall be traceable for the users, i.e., they shall have an option to see at least all changes made by themselves or others since the last 30 days.
10_03	Collaboration and Communication	It shall be possible to save visualizations as separate pages. These saved indicator state pages shall be sharable with others; so several users can have a look at it.

10_04	Collaboration and Communication	A saved indicator state page shall provide possibilities to textual communicate about it on the same page and link it with other data.
11_00	Integration and Interoperability	The system needs to be available to the user during teaching activities. So, the system shall be capable of being integrated in a course of a VLE.
11_01	Integration and Interoperability	The system's data model shall be prepared for including all relevant data of standard VLEs.
11_02	Integration and Interoperability	It shall be possible to integrated outcomes of single indicator request that have been calculated by the LA backend into a VLE, e.g., each indicator could have its own web page. This way, indicators can be provided as apps within app-based systems.
11_03	Integration and Interoperability	The system shall support single sign-on procedures, e.g., oAuth.
11_04	Integration and Interoperability	There need to be interfaces of the underlying data warehouse for importing externally collected data and and exporting the database of each indicator (e.g., for using it in SPSS / advanced user).
11_05	Integration and Interoperability / Permantlinks	Each question/indicator shall have a unique identifier (URL), in order to link to it for quick access during teaching activities within a VLE.
11_06	Integration and Interoperability / Permantlinks	Each state of an indicator, which is represented by a set of filtering values and the resulting visualization, shall be saved for later access, if the user chooses a related 'save this data for later access' button. This saved snapshot shall have a printable layout. Also it should be easy to include the snapshot in emails or slides (e.g. PDF or PNG format).

11_07	Integration and Interoperability / Permantlinks	A saved indicator state shall be accessible via a distinct link, so users can come back easily or reference to it, when discussing with others.
11_08	Integration and Interoperability	Integrate outcomes of central, standardized questionnaires into the system and let users choose if they want to visualize the results in their starting pages.
11_09	Integration and Interoperability	Indicators regarding specific modules of a course room (e.g. assignments) shall be integrable into that particular module in the sense that managers can access these indicators directly, when working with the module.
11_10	Integration and Interoperability	The system shall provide APIs for all elements, in order to be closely integrable into any VLE.
12_00	Openness, Extensibility, and Data Triangulation	The system architecture shall be open and allow for easy implementation of new indicators ideas.
12_01	Openness, Extensibility, and Data Triangulation	Users, who do not want to develop indicators themselves, shall have a form for specifying and requesting new indicators, if they do not find suitable ones in the list of all indicators.
12_02	Openness, Extensibility, and Data Triangulation	The LA development team and a data protection officer need to be included in all stages of the development process of new indicators.
12_03	Openness, Extensibility, and Data Triangulation	The system shall provide an export feature for the data of each indicator.
12_04	Openness, Extensibility, and Data Triangulation	The system shall provide the opportunity to triangulate data of differents sources with regard to the same question (e.g., combine usage statistics with a survey question). It shall be possible to compare quantitative results of indicators with results from surveys within the LA system (e.g., by

		integrating survey apps into the starting page).
12_05	Openness, Extensibility, and Data Triangulation	The system provides the option to add manually collected data (e.g., attendance numbers or exam results) to the database.
12_06	Openness, Extensibility, and Data Triangulation	Visualizations shall be interactive in the sense that users can add or aggregate data within the visualization, which is then stored in the database as manual data input, which can be used for other indicator results as well.
12_07	Openness, Extensibility, and Data Triangulation	The system should not narrow the view to certain data (e.g., don't focus questions/indicators only on usage data).
12_08	Openness, Extensibility, and Data Triangulation	The data model shall be easily extensible, if new types of data need to be incorporated. It shall to be designed in an open way, in order to include new data, resulting from innovative questions and innovative learning environments. For example, eLAT provides UserExtensions and AssetExtensions, in order to extend the predefined options.
13_00	Performance and Saving Time	The starting page, including the visualizations on it, need to have loading times less than a 60 sec. In order to reach this goal, it is advisable to pre-calculate questions/indicators and cache the respective visualizations.
13_01	Performance and Saving Time	The system shall estimate the duration for an indicator calculation and inform the users, who sent the particular request, about what is going on.
13_02	Performance and Saving Time	The system shall continue processing an indicator request, even if the user begins a new task. So, it allows the user, who sent an indicator calculation request, to work on other tasks during the waiting time. When finishing a report, the system shall inform the user about this.

13_03	Performance and Saving Time	At first use, the system should provide default selections of filtering items, which make sense for at least 80% of the courses, e.g., all filters should be selected by default.
13_04	Performance and Saving Time	The system should provide options to 'select all items', 'deselect all items', or 'select all item of type X' with regard to checkbox lists with more than 5 items.
13_05	Performance and Saving Time	Managers shall be able to select all questions from the list of all available questions at once.
13_06	Performance and Saving Time	The system shall provide a feature to get regular updates on the currents state of the data by email notifications.
13_07	Performance and Saving Time	The system shall store data in a suitable data warehouse so that it delivers excellent query performance, even for complex analytic queries.
13_08	Performance and Saving Time	All data visualization of questions, which have been added onto the starting page, shall be based on real data of the respective courses. The may be pre-calculated to make access to the monitoring views more efficient, e.g., these diagrams could show the latest reporting results that had been requested by the user (including the creation date).
13_09	Performance and Saving Time	Data visualizations shall highlight outliers of data clearly, so that users can immediately detect that there is something irregular about the visualization.
14_00	Storage / Data base / Data model	The data model shall include all relevant objects that need to be observed in a blended learning scenario, e.g., see eLAT data model.

14_01	Storage / Data base / Data model	The system needs to take into account established e-learning standards for its data model. It shall be independent of certain educational software, such as VLEs.
14_02	Storage / Data base / Data model	The implementation of the user interface (view) shall be independent from storing and calculating the data.
14_03	Storage / Data base / Data model	The system shall store the raw data results of indicators calculations, so different graphic web interfaces can interpret them, and results of different reports can be compared.
15_01	Question/ Indicator Request	How access is limited to certain learning materials before and after certain events, e.g., how do students access the learning materials before and after exercise group meetings?
15_02	Question/ Indicator Request	The ‘top 10’ indicator could also differentiate documents by types or folders (e.g., Top 10 Exercise Files)
15_03	Question/ Indicator Request	Dependencies between a teacher's activities and the behavior of students
15_04	Question/ Indicator Request	Detection of students at risk, if data privacy regulations and the situation allow for giving this information to the teachers.
15_05	Question/ Indicator Request	Correlate usage data with data related to success in midterm and final exams; Is there a relation between grades and usage patterns?
15_06	Question/ Indicator Request	How do different groups of (good, medium, bad) students study?

15_07	Question/ Indicator Request	How many students are active? A single bar, which presents the number of students, who have at least logged in once to access something, related to the overall number of registered students
15_08	Question/ Indicator Request	A notification subscriptions counter, which shows how many students are receiving email notifications about new items in the course
15_09	Question/ Indicator Request	How often have specific (folder/groups of) resources been accessed?
15_10	Question/ Indicator Request	Have learning materials been uploaded in sufficient time before the lectures?
	Question/ Indicator Request	For more indicator ideas see: Bültmann, M. (2011). Design und Usability-Studie eines Learning Analytics Werkzeugs. RWTH Aachen University. Dyckhoff, A. L., Zielke, D., Bültmann, M., Chatti, M. A., & Schroeder, U. (2012). Design and Implementation of a Learning Analytics Toolkit for Teachers. EDUC TECHNOL SOC, 15(3), 58–76. Dyckhoff, A. L., Lukarov, V., Muslim, A., Chatti, M. A., & Schroeder, U. (2013). Supporting action research with learning analytics. In Proc. of the 3rd International Conf. on Learning Analytics and Knowledge (LAK'13) (pp. 220–229). New York, New York, USA: ACM Press. doi:10.1145/2460296.2460340.