Learning Analytics Support in Higher-Education: Towards a Multi-Level Shared Learning Analytics Framework

Michael Vierhauser[1] [a], Iris Groher[2] [b], Clemens Sauerwein[1] [c],
Tobias Antensteiner[1] [d], and Sebastian Hatmanstorfer[2]

[1] *University of Innsbruck, Department of Computer Science, Innsbruck, Austria*

[2] *Johannes Kepler University Linz, Institute of Business Informatics – Software Engineering, Linz, Austria*

michael.vierhauser@uibk.ac.at, iris.groher@jku.at, clemens.sauerwein@uibk.ac, tobias.antensteiner@uibk.ac.at, k11805508@students.jku.at

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Abstract: Assurance of Learning and Competency-Based Education are increasingly important in higher education, not only for accreditation or transfer of credit points. Learning Analytics is crucial for making educational goals measurable and actionable, which is beneficial for program managers, course instructors, and students. While universities typically have an established tool landscape where relevant data is managed, information is typically scattered across various systems with different responsibilities and often only limited capabilities for sharing data. This diversity, however, significantly hampers the ability to analyze data, both on the course and curriculum level. To address these shortcomings and to provide program managers, course instructions, and students with valuable insights, we devised an initial concept for a *Multi-Level Shared Learning Analytics Framework* to provide consistent definition and measurement of learning objectives, as well as tailored information, visualization, and analysis for different stakeholders. In this paper, we present the results of initial interviews with stakeholders, devising core features. In addition, we assess potential risks and concerns that may arise from the implementation of such a framework and data analytics system. As a result, we identified six essential features and six main risks to guide further requirements elicitation and development of our proposed framework.

1 INTRODUCTION

In higher education, particularly at the university level, assessment of students' performance, systematic analysis of learning outcomes, and quality assurance of teaching and learning material have become widely adopted practices. Such activities even become mandatory when study programs apply for accreditation (e.g., AACSB[1] for business and accounting programs), which typically requires a set of well-established *Learning Objectives* on program-level and a course syllabus with an *Assurance of Learning* (*AoL*) system in place (Stewart, 2021). These objectives describe the competencies in terms of *skills* and *knowledge* (Kumar et al., 2023), learners (i.e., students) should have acquired after successfully completing the course (Vasquez et al., 2021).

In addition to meeting accreditation requirements, AoL serves as an effective quality assurance process for assessing the effectiveness of individual students, specific courses, and entire programs. To facilitate accurate evaluation, proper and well-defined measurements, as well as respective guidelines for improvements, need to be established. This requires support for the structured capturing and definition of metrics and evaluation data at both the program and the individual course level. Moreover, this contributes to the principle of *constructive alignment*, which emphasizes the alignment of Learning Objectives and teaching methods with the corresponding assessment (Mimirinis, 2007). Following this principle, for example, Learning Objectives need to be defined and subsequently linked on the program level as well as course level. Consequently, assessments need to be performed in a way so that student performance – with respect to the defined Learning Ob-

[a] https://orcid.org//0000-0003-2672-9230
[b] https://orcid.org/0000-0003-0905-6791
[c] https://orcid.org/0009-0009-9464-5080
[d] https://orcid.org/0000-0001-5513-1073

[1] https://www.aacsb.edu

jectives – can be adequately measured, typically requiring the aggregation and analysis of data from various systems. Furthermore, course enrollment data and student information may reside in a dedicated university-wide, centrally managed information system, whereas course data might be managed by different departments in dedicated *Learning Management Systems* (*LMS*), making it hard to create meaningful analysis, particularly on the program level.

Furthermore, to exacerbate the situation, Learning Objectives are often defined by different stakeholders for different goals and purposes. Program-level objectives are typically managed by program managers, while course-level objectives are defined by lecturers responsible for the individual courses. Knowledge about if and how course-level objectives do in fact contribute to program-level objectives is often overlooked and thus not captured (Lakhal and Sévigny, 2015). To draw meaningful conclusions, collected data needs to be analyzed to identify the skills and knowledge gained in the course and potential improvement areas, for example with respect to the didactic principles used or the course material provided (Bakharia et al., 2016): Program managers, on the other hand, might be particularly interested in historical enrollment data and cohort analysis to identify trends and plan courses accordingly, while instructors may seek to uncover knowledge gaps to improve their course setup, the material provided, or time spent on certain topics (Divjak et al., 2023). This calls for dedicated and customized views and visualizations of collected data, while precautionary measures need to be taken so that only eligible stakeholders have access to certain information (Pardo and Siemens, 2014).

As part of our ongoing work in the area of *Learning Analytics* (Clow, 2013; Khalil et al., 2022), we have created tools, scripts, and applications, for individual courses for basic analysis (e.g., analysis of students' competencies in programming classes), and therefore gained additional information beyond simple statistics provided by most LMS. However, keeping all of these up-to-date with ever-changing settings and exercise formats has quickly turned into a cumbersome and time-consuming experience, reinventing the wheel each semester for every new course analysis we introduced. To address these issues, we have developed an initial conceptualization of a *Multi-Level Shared Learning Analytics Framework* in order to build a comprehensive framework that provides extended analysis capabilities that provide information for students, course instructors, and program managers.

Following a proper Software Engineering process (Kotonya and Sommerville, 1998) for integrating the framework in the existing landscape of university-specific tools, workflows, and processes, in a first step we conducted a series of scoping interviews to (1) identify key stakeholders, and gain insights into current pain points and needs of students, course instructors, and program managers. As part of these interviews, we, furthermore, (2) collected high-level requirements and features users would expect to be provided by such a framework. Finally, we (3) collected potential risks or negative side effects, and what factors need to be considered when designing such a framework that might threaten its acceptance or readiness. Based on the results of the interviews, we have identified six feature categories and six risk groups that merit consideration in the development of our envisioned framework. Accordingly, we further discuss the findings and implications and lay out a roadmap for further development and evaluation in a university-wide process.

The remainder of this paper is structured as follows. In Section 2, we first present a motivating example from two universities facing similar challenges that led to the idea of creating a Multi-Level Shared Learning Analytics Framework. We continue by describing the interview study we conducted with key stakeholders in Section 3, followed by a discussion of the results and insights in Section 4. Based on our findings, we outline an initial roadmap for building our framework in Section 5.

2 BACKGROUND AND MOTIVATION

In this section, we first provide a motivating example (cf. Section 2.1) and discuss related work in the area of Learning Analytics and CBE (cf. Section 2.2).

2.1 Motivation for a Learning Analytics Platform

In recent years, *Competency-Based Education* (*CBE*) has gained significant traction at universities (Pluff and Weiss, 2022; Long et al., 2020). CBE is an educational model in which students pass courses that are part of their selected programs by demonstrating knowledge and skills (Vasquez et al., 2021). In these courses, students are typically assessed based on their ability to demonstrate specific competencies and, ideally, receive a more personalized learning experience tailored to their individual needs, preferences, and abilities. In order to transition to CBE and effectively implement CBE across all programs, it is crucial to systematically define learning objectives for both study programs and individual courses.

Learning Objectives are specific and measurable goals that describe what students should know, or be able to do by the end of a course or educational program (Teixeira and Shin, 2020; Barthakur et al., 2022). Learning Analytics, in this context, has been established as a major factor that provides deep insights and analysis (Atif et al., 2013; Klein et al., 2019; Viberg et al., 2018). A key factor for successfully introducing competencies and CBE is the ability to measure learning outcomes, analyze data, and draw conclusions to improve both students' results and curriculums. As part of our own work in this area, we have been directly engaged in the accreditation of course programs in business informatics and business administration, and have further introduced competencies and dedicated LOs in our undergraduate basic programming courses.

However, as part of this effort, we have faced multiple challenges and pain points with regard to defining competencies across several courses of a study program, and more importantly, creating meaningful analyses that go beyond "simple" course-level analysis. In accrediting business informatics and administration programs, we introduced competencies and dedicated LOs, and faced significant challenges in defining consistent cross-course competencies. Particularly, we experienced difficulties with data interconnectivity across university systems, complicating course analysis, planning, and budgeting. One of the first issues we encountered was a *lack of interconnectability* and the ability to exchange and aggregate data between various university systems. For example, in order to create meaningful gender analysis of course and exam results we had to manually export student data from the university management system and exam data from our LMS and merge everything in an Excel spreadsheet, which we, at some point, automated using various self-written Python scripts. Similar problems arose when trying to collect information about students progressing over several semesters to get insights on how to plan our upcoming courses (particularly with regard to slots we need to offer and course instructors we need to budget). During discussions with colleagues from other departments and universities, we found that many have encountered comparable hurdles when attempting to implement Learning Analytics that go beyond the limited functions provided by current tools. Even though the specific tools (e.g., LMS and university information systems) are different, challenges remain largely the same.

2.2 Related Work

Learning Analytics is driven by the ever-growing availability of data and the rise of online learning and corresponding learning platforms, that allow tracking students and collecting vast amounts of learning-related information (Ferguson, 2014). In recent work, Tsai *et al.* (Tsai et al., 2020) have identified trends and barriers in applying Learning Analytics in higher education. Similar to our intentions, "improving student learning performance" and "improving teaching excellence" rank among the most important driving factors. With regards to skill descriptions part of LA activities, Kitto *et al.* (Kitto et al., 2020) have explored the use of skills taxonomies establishing mappings between different subject descriptions using natural language processing. This aspect is also highly relevant in the context of our framework, helping to not only standardize the curricula formats, but also automate the mapping. Focusing on curriculum analytics, Hilliger *et al.* (Hilliger et al., 2020) have create an "Integrative Learning Design Framework" and accompanying tool support. Their work focuses on instructors and curriculum managers as primary stakeholders and supports program-level decision-making. Their insights on these two levels, e.g., the need for "automated reports of competency attainment" are also useful input for further requirements for our framework.

Gašević *et al.* (Gašević et al., 2016) conducted a large-scale study on LMS usage and student performance. One of their main findings was that too generalized models for academic success used in Learning Analytics may not improve the quality of teaching, and that more course-specific models could be beneficial. Moreover, Ifenthaler and Yau (Ifenthaler and Yau, 2020) have conducted a systematic literature review, including 46 publications on Learning Analytics support in higher education. Similar to our anecdotal evidence, they concluded that standardized measures, and visualizations are needed, that can be integrated into existing digital learning environments. Kumar *et al.* (Kumar et al., 2023) suggest a model for computer science curricula that integrates knowledge and competency models synergistically. Their work focuses on both ends of the learning spectrum, facilitating on the one hand teaching and on the other hand assessment. Consequently, Kumar *et al.*'s model offers both "an epistemological and a teleological perspective" on the subject of computer science, thereby guiding ongoing specification and refinement of our proposed Multi-Level Shared Learning Analytics Framework.

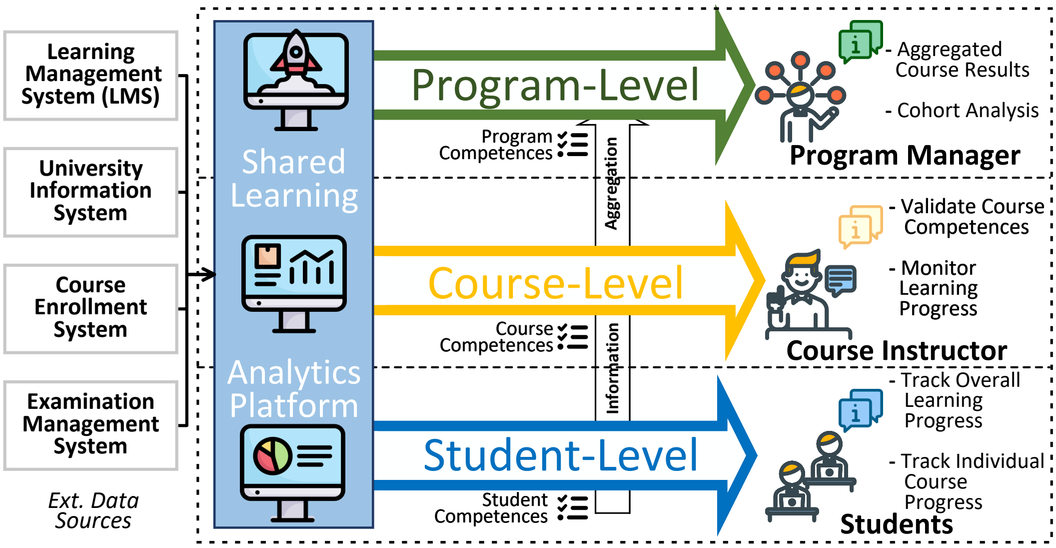

Figure 1: Our envisioned framework with 3 levels (i.e., student, course instructor, program manager) with customized visualization and analysis capabilities.

3 INTERVIEWS

As a first step towards collecting core requirements and identifying additional key stakeholders, we conducted a series of initial semi-structured interviews with participants from two different universities in Austria. The goal was to gain insights and a deeper understanding of the current situation, pain points, and high-level requirements and features of such a framework. Moreover, we sought to identify potential risks when introducing such advanced analytics capabilities that process potentially sensitive data.

In the following, we provide details about our proposed framework (cf. Section 3.1), the interview setup (cf. Section 3.2) and results (cf. Section 3.3).

3.1 Conceptual Framework

Based on the identified shortcomings and issues we have observed, we developed an initial concept of a *Multi-Level Shared Learning Analytics Framework* that aims to assist both program managers and course instructors. In addition, our proposed framework should provide students with information about their study and learning progress. Fig. 1 provides an overview of our envisioned framework, depicting its three main levels: At the bottom level, individual students should be supported (Rainwater, 2016), for example, throughout the course of a semester to keep track of their learning progress, whereas at the course level course instructors should be able to keep track of their class and identify potential shortcomings or weak points early on. At the top level, a program manager in charge of one or more programs needs a comprehensive, literally high-level view of multiple courses, with aggregated metrics and LOs.

• **The Student-Level.** Learning Analytics not only provides benefits to teachers and instructors, but can also provide valuable information to students. Similar to an LMS where students have access to course materials, students can explore the competences of each individual course in which they are enrolled in. Moreover, they receive immediate feedback about the competencies they already gained, and successfully completed assessments, assessments they have successfully completed, assessment results, and upcoming tasks.

• **The Course-Level.** Course instructors use the framework to define and manage course objectives and link them to assignments and related teaching and learning materials. This allows for a more detailed examination of the extent to which students are achieving each course competency. In addition, validation of the coverage of all competencies in a particular given course is provided. Furthermore, to support a top-down analysis, instructors link their individual course objectives to the overall program-level objectives.

• **The Program-Level.** At the highest level, program managers use the framework to define and manage program objectives which, in turn, are linked to the individual course objectives. They are provided with a view that shows how each course in the program contributes to these objectives. In addition, high-level views and analysis of course results support identifying in which order students complete the courses and what difficulties they face.

• **Integration of External Data Sources.** To provide the above-mentioned analysis capabilities, different external data sources need to be integrated, including LMS as well as university management, course enrollment, and examination management systems. In this way, LOs can be linked to teaching and learning material, homework assignments, or assessments. Moreover, detailed access statistics can be presented to course instructors.

3.2 Methodology

The objective of the preliminary scoping interviews was to gather the prerequisites for our proposed framework while obtaining explicit comprehension of the needs and requisites of stakeholders at different levels. Therefore, we specifically selected participants representing stakeholders at three different levels, i.e., students, course instructors, and program managers (cf. Fig. 1).

One researcher created an initial set of questions, which was then discussed among the authors, and the final questionnaire was divided into three parts, with a total of 14 open-ended questions. In the first part, we asked participants about their current practices and tasks they conduct specific to their respective roles and if any tool support exists. After this, we briefly introduced the concept of our Multi-Level Shared Learning Analytics Framework (cf. Section 2.1 and Fig. 1). We intentionally refrained from introducing the framework before part one to avoid any bias when discussing the current state.

The second part focused on the framework requirements and features, as well as potential issues or risks that may arise when introducing such a framework. Finally, the third part was dedicated to the individual stakeholder's level and what – as well as how – they would use the proposed framework in their daily professional life.

In total, we conducted interviews with twelve participants, i.e., four per level, with two at each of the two universities. For the student level, we covered a broad spectrum of both bachelor and master students of Business Informatics as well as Computer Science. For the course level, we interviewed three senior lecturers with several years of teaching experience, and one Assistant Professor. Finally, for the program level, we interviewed three professors, who also serve (or have served) as program managers for various programs ranging from bachelor to PhD programs, and a program/accreditation manager. Each interview was conducted by at least one researcher in person or via Zoom, lasting approximately 45 minutes to one hour. After asking for consent, we recorded all interviews and subsequently transcribed them using *OpenAI*'s Whisper speech-to-text service (OpenAI, 2023). All interviews were conducted and recorded in German and later partially translated during coding (see below).

After the transcription of the interviews, we used open coding to analyze them for relevant information about (1) features, (2) stakeholders, or (3) potential risks and challenges (Seaman, 1999). For this qualitative analysis of the interviews, we used *QCAmap* (T. Fenzl and P. Mayring, P., 2023), an open-source tool for systematic text analysis. Relevant statements were then translated into English, and two researchers subsequently created an initial grouping of the codes. In the second step, two additional researchers reviewed the initial grouping, conflicts were resolved, and the final grouping was established. All researchers are co-authors of this paper with experience in teaching, Learning Analytics, and interview studies.

3.3 Interview Results

After multiple iterations of discussion among the researchers a final set of feature and risk categories emerged. In total, we identified twelve categories. Six categories pertaining to potential features and framework requirements (cf. `F01` to `F06`, and another six (cf. `R01` to `R06` in Table 1) concerning potential risks and challenges. An overview of the final set of categories and number of constituent codes is provided in Table 1.

Statements covering features are split fairly evenly across five categories, with only the sixth group related to "Course Harmonization" was only mentioned four times. For the stated risks, two categories stand out. First, (general) "Platform Usage and Operation" was mentioned 21 times, and second, privacy and data protection issues were addressed a total of 16 times. In total, we included 238 coded statements, which are distributed across the twelve groups `F01` to `F06` and `R01` to `R06`. As 22 statements were not explicitly assignable to one group, but fit into two groups, we assigned them to both. In addition, for each code, we also attached the relevant levels to identify cross-cutting features and risks.

In the following, we discuss each of the feature and risk categories in more detail.

4 DISCUSSION

In the following section, we provide an overview of the results from our interviews, first discussing the resulting feature categories (cf. Section 4.1) and second the risks we have identified (cf. Section 4.2) .

4.1 Feature Categories

Based on our analysis and coding, we uncovered six main categories of features that were mentioned during the interviews. The five features *Curriculum Management Support*, *Quality Assurance*, *Study Planning*, *Study Statistics*, and *Course Harmonization* cover specific framework functionalities, whereas *System Integration*, collects functionality not directly provided by our envisaged framework, yet vital for its intended application.

• **Curriculum Management Support.** One major group of requirements revolves around the curriculum and curriculum-related activities that are necessary to manage and maintain a study program. While such activities fall within the responsibilities of program managers, interviewees have mentioned several aspects where our proposed framework could also support course instructors as well as students as a positive side effect. For example, tracing and refining existing program-level Learning Objectives could help them to better plan their individual courses, or a single view on university processes can alleviate the (administrative) burden of credit transfers, for both students and course instructors alike (e.g., Learning Objective-related recognition rules responsibilities). This confirmed our assumption that dependencies across different levels of our framework are of particular importance, and that functionality on one level could also be beneficial for other stakeholders not directly involved in a particular task.

• **Quality Assurance.** Several requirements cover topics related to quality assurance, such as support for accreditation of study programs, and consolidated information necessary for this process. Furthermore, participants mentioned the importance of performing cross-course analysis, as well as cohort and enrollment number analysis. The framework should thus provide different metrics from dropout rates in courses, to a detailed display of already completed introductory courses. It should also make Learning Objectives "quantifiable", facilitating measurability, and identifying problematic Learning Objectives. An identification of lower-performing students would allow for early intervention strategies. Moreover, interviewees mentioned that "*(the framework) can really make Learning Objectives measurable and operationalized, so that they are not only just defined.*"

• **Study Planning.** Another group of requirements is related to the organization and planning of courses for study programs. Scheduling courses and exams typically falls within the responsibility of program managers, and the framework could help them optimize resource utilization by suggesting the optimal size and timing for specific classes. Participants mentioned that dependencies between courses and their objectives can be visualized, which might help them to schedule courses in a sequence that maximizes learning outcomes while minimizing schedule conflicts. This can also foster exchange or coordination between teaching staff regarding the contents to be taught, or material to be provided in courses. The study planning feature is also relevant to students. The students interviewed indicated creating a customized study schedule based on their enrolled classes, taking into account due dates for assignments and exams would be very helpful. In addition, students stated that they might also like to monitor their own study progress by visualizing course dependencies or prerequisites to make more informed decisions about which courses to take in future semesters.

• **Study Statistics.** Particularly, the group of course instructors suggested that the use of statistical analysis can provide sophisticated information about students and their learning progress. For example, key performance indicators (KPIs) to measure homework assignments, and aggregated course and grade statistics for students might be beneficial. Moreover, potential features of the framework highlighted by instructors' respondents include linking competencies to homework or exam questions and comparing homework or learning objectives. Similarly, students mentioned that measuring or checking their learning progress, statistically analyzing their learning goals, and gaining insight into their learning progress would be valuable in assessing their current learning performance.

• **Course Harmonization.** Program managers, instructors, and students unanimously identified transparency as a crucial feature of the envisioned framework, highlighting the potential of our framework to enhance course evaluation and establish uniform as-

Table 1: Resulting Feature and Risk categories.

	ID	Category Description	Count
Features	F01	Curriculum Management	51
	F02	Quality Assurance	49
	F03	Study Planning	56
	F04	Study Statistics	44
	F05	Course Harmonization	4
	F06	System Integration	56
Risks	R01	Preconditions not met	8
	R02	Negative side-effects	4
	R03	Interpretation of Data	4
	R04	Privacy	16
	R05	Platform Development	6
	R06	Platform Usage & Operation	21

sessment criteria and standards across classes. For example, one participant mentioned that it would be good to have "*[...] uniform and somewhat comparable grading criteria for different classes*".

• **System Integration.** Due to the multitude of tools and heterogeneous platforms used at the program, course, and student level, it became evident that system integration was the most frequently cited feature. This requires interface functionalities to other systems (e.g., LMS, and university information systems) or the ability to (automatically) import/export data relevant for analysis. On the other hand, corresponding communication functionalities have also been demanded to enable uniform communication between lecturers and students, or vice versa.

Concerning the three levels of our proposed framework (cf. Fig. 1) we were able to identify specific activities and hence requirements for each of the anticipated user groups. For the program level, curriculum management, and study planning-related activities were mentioned most frequently (cf. *Curriculum Management Support* and *Study Planning* features). While currently tools exist that support (parts) of their work in this area, spreadsheets, and manual work still appear to be prevalent. For the group of course instructors and students, we could identify a broad level of planning and analysis activities. The unified view on several courses was deemed helpful by both groups and could help either group to gain additional insights into their teaching and study activities.

4.2 Identified Risks

Besides the desired features, the second aspect of the interviews was concerned with identifying potential risks and negative implications such a framework could exhibit.

As the envisioned framework potentially combines and manages electronic data about students and their study progress, data protection, and privacy were consistently cited as one of the main risks by all three groups. Depending on the level of the respondent, different aspects of data protection were considered important. For example, there should only be role-based access to data, even though the data is scattered in different systems and needs to be shared accordingly. This might pose a major challenge, as it would mean standardizing access controls, role management, and even establishing a decentralized security infrastructure.

Furthermore, participants identified data misinterpretation as another major risk. Learning Analytics platforms collect and analyze large amounts of data to provide insights into student performance, commitment, and Learning Objectives. However, the interpretation of this data can be challenging. Oversimplification of data visualizations, and unsuitable metrics may inadvertently introduce biases, leading to unfair or inaccurate assessments of student capabilities. Also, looking at certain KPIs in isolation may not capture the full context of a student's learning journey, potentially resulting in misleading conclusions. Excessive dependency or focus upon KPIs was stated as one specific risk: "*result in [...] focusing too much on KPIs, which are continuously checked, with the purpose to have students pass a class, and push them through - but they might lose interest in studying/learning something new*." Without a profound understanding of the educational context, stakeholders may make ill-informed decisions based on the presented data.

Another risk is related to how to use the available data, for example, the aggregated course information or student performance. While such data can improve quality and learning outcomes (cf. Quality Assurance), over-reliance on statistical data and KPI-related metrics without critical reflection could hinder creativity and individual teaching approaches. Furthermore, specifically by the lecturers, the fear was expressed that aggregated information can serve as a monitoring tool for lecturers, and thus it has to be clearly defined which information can be viewed by which stakeholders.

Concerning the framework's utilization and functionality, risks arise from potentially low acceptance among stakeholders. Consequently, additional commitment is warranted to overcome the complexity and possible ambiguity of the framework. Furthermore, it may not be perceived as having significant advantages, as "*it simply presents already available information more streamlined*".

4.3 Threats to Validity

As with any study, our work is subject to a number of threats to validity.

The number of study participants was limited, which constitutes a threat to external validity. In total, we interviewed twelve participants – four from each level of the envisioned framework. However, all participants had several years of experience within their area of expertise, and we included participants from two different universities.

To gain a broader understanding of detailed requirements and needs in such a framework, further interviews are required. Nevertheless, we are confident that our initial interview study has captured a number of highly relevant features and requirements for further discussion and refinement. While we have focused on the educational and learning needs of Computer Science and Business Informatics, we believe that our framework can be applied in a broader context. To further confirm the generalizability of the features, additional evaluation is needed, for example in the form of a dedicated utility study of individual features.

Concerning internal validity and analysis and interpretation of results, several researchers were involved in the process. The extracted interview data was extensively discussed among all researchers and groupings, features, and respective risks were discussed until consensus was achieved.

5 ROADMAP

Our interviews have confirmed a pressing need for additional support and tools to facilitate AoL at the course and curriculum level. Furthermore, as we expected, privacy and (mis-)use of data were mentioned as one of the primary concerns, alongside the acceptance and adoption of yet another tool in practice.

One surprising takeaway from the interviews was that certain features, we assumed would be beneficial for a particular group of stakeholders, (e.g., course instructors) would be equally valuable, for example, for students when presented (i.e., visualized) in a slightly different way. Another important aspect is the incorporation of existing university processes where the framework needs to be embedded. While individual Learning Analytics solutions require less "global" (i.e., university-wide) effort, connecting and analyzing data across courses, or even study programs, needs to take into account existing roles and their respective responsibilities (e.g., dean of study who is in charge of overseeing several programs). Based on our findings and observations from the interviews, we have compiled three main tasks as part of our next steps that will provide (1) a data protection concept and transparency guidelines, (2) an information model for relevant data and roles, and (3) a reference architecture and implementation.

• **Interfaces & Data.** Visualizing and analyzing data was deemed as one of the key aspects, requiring the integration of various interfaces and external data. Initial steps include a detailed analysis to identify key systems, the information they offer, and the derivation of a relevant information model. The ability to visualize and analyze data, was deemed as one of the key aspects. This in turn requires diverse interfaces and external data to be integrated. One of the first activities will be an in-depth analysis, identifying key systems and what kind of information these can provide and deriving an information model of relevant data.

• **Data Protection and & Privacy Concept.** As interview participants have indicated clear concerns regarding data protection and the threat of data being available to a (too) broad range of users, a key activity – interconnected with the information model – is the creation of a role and access concept guided by existing university processes and access rights. This will allow us to specify what data is required and who will be eligible to view certain information or statistical analysis. In addition, to mitigate the fear of misuse, transparency is a second key factor. We will work on creating clear guidelines on what information is provided, how it is used, and how it can be used (e.g., only in anonymized and aggregated form).

• **Learning Objective Definition & Management.** The effective management of learning objectives, both on curriculum and on course level, is a central part of our proposed framework. Learning Objectives will be systematically defined using a standardized taxonomy, such as Bloom's Taxonomy (Thompson et al., 2008; McNeil, 2011), to ensure clarity and measurability. They will then be mapped to specific learning activities and assessments, facilitating tracking and analytics.

As part of these activities, we are planning on conducting focused workshops with stakeholders to perform a more in-depth requirement elicitation. Based on an initial proof-of-concept prototype, we are currently building based on the collected features, we will follow a participatory design approach (Trischler et al., 2018) to actively engage users from all three levels, in all phases of the design. One concrete outcome from this second analysis is a reference architecture of our framework that will serve as a blueprint for implementing interfaces and a concrete framework instance.

6 CONCLUSION

In this paper, we have presented findings from a series of preliminary interviews, with the main aim of collecting requirements for a Shared Learning Analytics Framework. In summary, our investigation has revealed essential insights into the characteristics and potential hazards associated with such a framework. We identified six fundamental features, related to curriculum management, study planning and statistics, quality assurance, course harmonization, and integration of other systems. Moreover, stakeholders highlighted six critical risks that could impede the adoption of such a framework, ranging from privacy concerns to development and maintenance challenges, along with potential negative side effects. Building upon these initial findings, our next steps involve conducting focused stakeholder workshops to further refine and extend our requirements and subsequently derive a comprehensive design and reference architecture.

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