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Unleashing Process Mining for Education: Designing an IT-Tool for Students to Self-Monitor their Personal Learning Paths

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Abstract. The ability of students to self-monitor their learning paths is in demand as never before due to the recent rise of online education formats, which entails less interaction with lecturers. Recent advantages in educational process mining (EPM) offer new opportunities to monitor students' learning paths by processing log data captured by technology-mediated learning environments. However, current literature falls short on providing user-centered design principles for IT-tools which can monitor learning paths using EPM. Hence, in this paper, we examine how to design a self-monitoring tool that supports students to evaluate their learning paths. Based on theoretical insights of 66 papers and nine user interviews, we propose seven design principles for an IT-tool which facilitates self-monitoring for students based on EPM. Further, we evaluate the design principles with seven potential users. Our results demonstrate a promising approach to help students improve their self-efficacy in their individual learning process using EPM.

Keywords: Educational Process Mining, Self-Regulated Learning, Technology-mediated Learning, Personal Learning Paths, Design Science Research

1 Introduction

Recently, the application, and thus the relevance, of technology-mediated learning (TML) environments [1], such as the embedding of offline lectures in learning management systems (LMS) or the availability of massive open online courses (MOOCs) [2], has increased. According to Dahlstrom et al. (2014) [3], 99% of U.S. colleges and universities organize their pedagogical scenarios in standard LMS. Not only the organization of courses in LMS but also the embedding of TML tools are expected to continuously grow during the upcoming years to a market size of $336.98 billion by 2026 [4–6]. Examples of those TML tools are intelligent tutoring systems (i.e., [7]) or computer-supported collaborative learning tools (i.e., [8]). Yet educational institutions and educators still struggle to provide students with ongoing support and individual feedback, especially in large-scale and distance learning settings, due to organizational and financial constraints [9]. Several studies have revealed that the lack of individualized support leads to low learning outcomes, high dropout rates, and dissatisfaction with the overall learning experience [10–12]. Especially due to the abrupt increase of distance-learning scenarios at schools and universities through COVID-19, many students had difficulties organizing and controlling their own learning process [13, 14]. Therefore, scholars have called for intensive research to investigate how to assist learners in cultivating monitoring their learning progress, especially in distance learning scenarios [15].

Against this backdrop, the integration of learning processes in TML environments offers a promising opportunity to capture and process data about the student's learning behavior, learning activities, and thus, learning processes at different granularity levels. A learning process consists of different activities that a student is (or is not) endeavoring to reach a specific learning goal and outcome (i.e., [16]). TML environments offer the potential to capture digital traces from these processes, such as event logs (e.g., starting or ending event of a particular exercise at a certain time), textual data (e.g., written essays), comments on learning content, or measured learning outcomes (e.g., a student's skill level after taking an assessment).

One approach promising to better analyze and monitor digital traces has recently gained momentum through industry applications. Educational process mining (EPM) uses log files of learning data to discover, monitor, and improve self-organized learning processes [4]. Therefore, EPM can process the learning data of different TML environments and might be, therefore, a useful approach to monitor personal learning processes. Recently, research has shown that such monitoring of students' learning processes in TML environments based on EPM can increase students' self-regulation abilities and foster their learning outcome and performance (i.e., [15, 17]). Further, Nguyen et al. (2020) [18] lay the foundation for the design of such a monitoring tool, but only include theoretical requirements. However, the authors suggest *"consider the importance of end-user experience"* (p.18) for the design of a self-monitoring tool for students [18]. However, to the best of our knowledge, current literature falls short of providing a user-centric design approach of an IT-tool based on EPM for students to monitor their learning process. Therefore, we propose the following research question (RQ):

RQ: *What are user-centric design principles for designing an IT-tool for students to self-monitor their learning process based on educational process mining?*

We address the research question by following the design science research approach (DSR) by Hevner (2007) [19]. There is a current lack of design knowledge for using educational process mining for students' self-monitoring during learning processes. We intent to design and evaluate an IT artifact grounded on the self-regulated learning theory by Zimmerman [20–22]. Current research shows that the self-regulated learning theory can illuminate the use of an IT-tool for self-monitoring to improve students' learning progress [23]. This theory has often been applied in the context of educational process mining for self-monitoring of students' personal learning paths (e.g., [17, 24, 25]). Our contribution is accomplished by applying theory and deriving user-centered design requirements for the development of an EPM tool to improve students' self-monitoring and evaluation capability based on self-regulated learning theory. In this paper, we introduce our preliminary design principles (DP) that we derived from literature and from conducting student interviews of one master course. Further, we evaluated these DP with seven potential users and refined the DPs. Our results can help practitioners and educators to design user-centric IT-tools for students that facilitate self-monitoring of their learning path by use of the trending technology EPM.

2 Theoretical Background

2.1 Educational Process Mining

Recently, EPM is becoming a popular concept for the processing of learning data from TML environments [4, 5]. Nevertheless, it is still a relatively young research field, which evolved from business process modeling [26]. Process Mining leveraged the discovery, analysis, and improvement of business processes based on event log data and is currently finding applications for learning processes [17]. Whereas the two related concepts for the analysis of learning data, namely educational data mining and learning analytics, are more data centric, EPM is more focusing on the learning processes and uses log data to incorporate data from different learning sources [27]. EPM specifically aims to extract insights from these event logs that are stored by TML environments [17], and therefore can achieve a deeper understanding of students' learning paths (e.g., [28]). Event logs in the educational context usually comprise different types of data, among others, mouse gestures, time stamps, click streams, chat logs [4]. PM in education processes these event logs from various data sources and then combines techniques of model-based and data-oriented analysis to discover, monitor, and improve learning processes [29, 30]. Therefore, EPM is a beneficial approach for monitoring students' learning process by processing personalized data from the TML environments. Hence, EPM should not only serve for depicting personal learning paths but monitoring the process and providing feedback in real-time, e.g., by building visualization tools or recommending personal learning paths [31].

For EPM, three different basic types of PM can be distinguished [4, 26]:

- **Process discovery:** modeling and visualizing the learning process of students, e.g., in order to monitor a student's individual learning journey or the curricular path a student takes.
- **Conformance checking:** analyzing whether an observed learning process conforms with a pre-defined learning process model, e.g., in order to identify weaker students (outliers) or analyze conformance with guidelines and prescriptions.
- **Process enhancement:** extending a given learning process model based on information extracted from a specific event log related to the same process,

e.g., to detect bottlenecks or provide students adaptive feedback on their process.

2.2 Personal Learning Paths

Traditional technology-mediated online environments, such as e-learning or LMS, often provide un-personalized learning material and do not navigate users through their learning process [32]. Self-directed learners require more time to assess and choose suitable learning materials [33]. A new form of online educational environments, like intelligent tutoring systems are interactive and can personalize learning processes suited to personal requirements, characteristics, and pace of learning [34]. EPM provides the great potential to monitor these personal learning paths. For instance, Uzir et al. (2020) [35] used PM for the analysis of students' personal learning paths, including monitoring of paths, the usage of learning resources or navigating the learner in the learning environment. Besides, Wang et al. (2018) [36] apply PM to monitor the learning processes of students and offer personal course sequences.

2.3 Self-regulated Learning Theory as a Kernel Theory

The self-regulated learning theory developed by Zimmerman examined learning characteristics from a meta-cognition, motivational and behavioral perspective [20, 37]. Zimmerman (2002) defines self-regulated learning as *"the self-directive process by which learners transform their mental abilities into academic skills*" [22] (p.18). Self-regulation is a cyclic process, which in general contains the three phases: (1) the forethought phase comprises task analysis and strategic planning, as well as goals setting and outcome expectation, (2) the performance phase includes self-control and self-instruction during the learning processes, and (3) the self-reflection phase contains self-evaluation as well as self-reaction on the learning process [22].

Especially in online learning formats, the self-regulation abilities of students are important, because they have less interaction with the lecturer [38]. Bandura (2001) examines that two components of self-regulation -self-monitoring and self-evaluation- in learning processes are important to increase the self-efficacy of learners. Self-monitoring and self-evaluation help learners to become aware of their strengths and limitations in their current learning behavior, as well as to consciously reflect on their learning progress and strategy [15, 22, 38]. Consequently, students with high self-monitoring abilities are less likely to fail or dropout of online courses [39]. Further, there are two different theories in relation to self-regulated learning, which are vital to include to support a self-regulated learning tool. First, cognitive load theory by Sweller et al. (1994) argues that working memory of each learner has a limited capacity and therefore must be paid attention during self-regulated learning [40]. Second, the dual channel theory by Moreno & Mayer (2007) [41] argues that self-regulated information processing of learners improves when pictures and words are included. Thus, designing IT-tools that support students to self-monitor their learning paths is a beneficial approach to increase students' learning performance in TML environments.

3 Research Methodology

The main goal of this study is the development of user-centered DPs for the design of a self-regulated learning tool based on educational process mining. Thus, we follow the DSR approach of Hevner (2007) [19] to contribute to the existing body of design knowledge based on the current knowledge base and user perceptions. Figure 1 shows the conducted steps of the DSR approach.

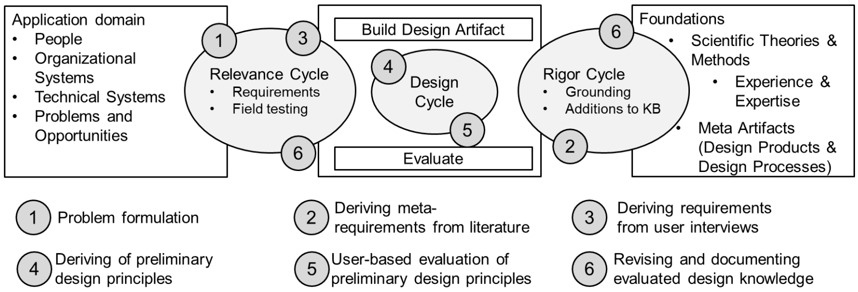


Figure 1. Three cycle design science process according to [19]

The first step of the DSR cycle contains the problem formulation. Therefore, we explained the relevance of the practical problem in the introduction of this paper. As the second step, we considered recent academic literature to derive a set of meta-requirements for the design of a student-centered EPM tool. In the third step, we conducted nine semi-structured interviews with master students based on the approach of Myers and Newman (2007) [42]. Thereby, we congregated user stories and user requirements for the design of a EPM tool for students self-monitoring based on Cohn (2004) [43]. In the fourth step, we derived the DPs based on to previously determined set of user requirements. We used the proposed structure by Gregor et al. (2020) [44]. The fifth step included an ex-ante evaluation, which we conducted based on the evaluation criteria of Venable et al. (2016) [45]. We evaluated the DPs with the criteria relevance, utility, and robustness to see how students perceive the value of every preliminary DP. Additionally, we asked open question to gather improvements and change requests. Therefore, we conducted a survey-based evaluation with seven potential end users, which are all students on master level. We included feedback and change requests from the evaluation to refine the DPs. In the sixth step, we revised and documented the evaluated design knowledge.

4 Designing and Evaluating the Artifact

Based on the problem formulation in step one, in this section we will describe and discuss how we congregated the preliminary requirements, derived our six preliminary DPs and evaluated them. Changes are marked as underlined in the figure. DP 7 was added after the evaluation. The main requirements are illustrated in figure 2.

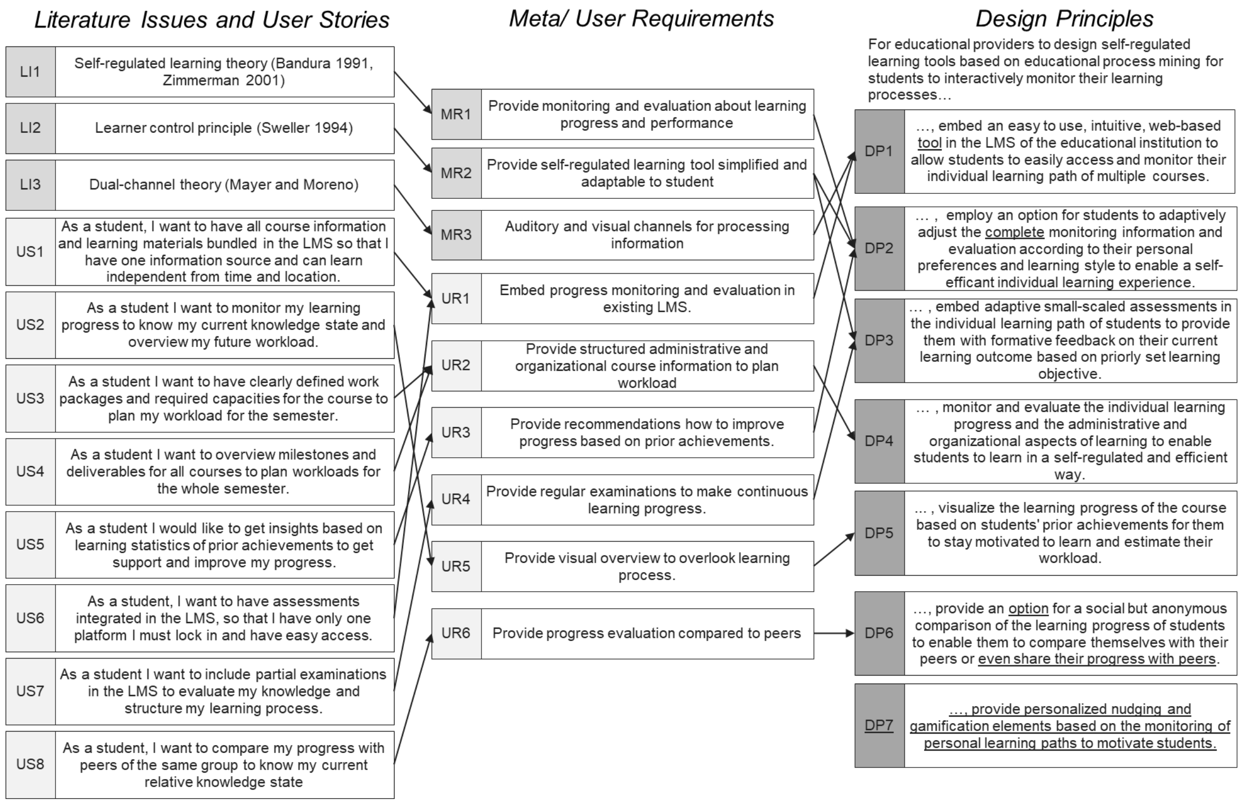


Figure 2. Overview of the derived design principles according to [44]

4.1 Defining Meta-Requirements from Scientific Literature

We collect meta-requirements from scientific literature for the development of the EPM tool for self-monitoring. To do so, we conducted a systematic literature review according to Webster & Watson (2002) [46] and vom Brocke et al. (2015) [47]. The overall scope of the conducted review can be defined along the dimensions of process, source, coverage, and techniques [47]. Based on recent literature reviews on EPM (e.g., [4, 48], we identified different keywords, which researchers used to describe PM in the educational domain. Based on the keywords, we built the following search strings: "[Process Mining" OR "Workflow Mining" OR "Task Mining"] AND ["Education" OR "Learning Analytics" OR "Training" OR "Skill Development" OR "Student" OR "Teaching" OR "Learner" OR "Pedagogic" OR "University"]. We identified three broad areas for deriving studies on EPM – IS, HCI and educational technology – as they cover a substantial share of the literature on our phenomenon of interest. To find relevant literature of studies that applied PM in educational scenarios, we applied the search strings to the following six databases: AISeL, EBSCO, Science Direct, ProQuest ABI Inform, IEEE Xplore, and ACM Digital Library. The database search resulted in 2885 hits. Titles, abstracts, and keywords were screened to fit the abovementioned definition and application to the scope of our study. We excluded papers that did not refer to PM or that applied PM in another domain than education. Multiple papers were excluded due to a different research scope described in their abstract, e.g., several papers described mineral mining or machine learning and PM outside of an educational setting and thus were eliminated from our sample. This screening process resulted in 66 relevant empirical papers that mentioned that they applied PM in education in the course of their study. Based on our kernel theory (*self-regulated learning theory*), we derived three literature issues (**LI**).

The first literature issue (**LI1**) is deducted from Bandana et al. (2001) and Zimmermann et al. (1990, 2002) [20, 22], arguing that self-monitoring and self-evaluation increase the self-efficacy during learning processes. Hence, it is vital to provide students the possibility of monitoring and evaluating their learning paths and progress (**MR1**).

Furthermore, based on cognitive load theory by Sweller (1994) [40], Mayer and Moreno (2003) [49] defined an e-learning theory with a set of principles on how educational technology can be used and designed to promote effective learning (**LI2**). Besides different principles we incorporated in our design of the initial prototype, the learners' control principle (**LI2**) is of special significance for learning metacognition skills, since it aims to enable learners to adjust the amount of input information needed for their personal learning process (**MR2**). Moreover, based on Mayer and Moreno's (2007) [41] dual channel theory, students learn more from pictures and words then from pictures or words alone (**LI3**), therefore the tool should provide auditory and visual channels for processing information (**MR3**).

4.2 Defining Requirements from User Interviews

After we derived Lis and MRs, we conducted nine semi-structured interviews with students according to Myers & Newman (2007) [42]. The interviewed users were a subset of students from one master course at our university, because they have long-lasting learning experience and have been going through the same learning process in the course. Interviews lasted between 20.19 and 41.42 minutes. The guideline comprises 24 questions and included the following topics: experience with technology-mediated learning systems, Self-awareness of own learning progress, needs and requirements for self-monitoring and self-evaluation during learning process, requirements for an EPM tool that supports self-regulated learning. Based on the results, we gathered user stories (**USs**) and identified seven user requirements (**URs**) following Cohn (2004) [43].

The first user story of students (**US1**) reflects their need to have all course information and learning materials bundled in one LMS so that they have one information source and can learn independent from time and location. Hence, the progress monitoring and evaluation tool should be embedded in an existing LMS (**UR1**). All students stated that they want to monitor their learning progress to know what their current knowledge level and overview future workloads (**US2**), which is reflected in **UR5**. Moreover, all students want to have a clearly structured administrative and organizational course information (i.e., defined course workload, milestones, deliverables) (**US3**, **UR3**) communicated in the beginning of the course to plan their study times (**US4**). A majority of students mentioned that they would like to get insights and recommendations on their learning progress (**US5**), which was included in **UR3**. Further, most students wanted to have partial examinations and assessments during their learning process to evaluate their learning progress (**US6**, **US7**), which was incorporated in **UR4**. Many students additionally wanted to compare their learning progress with peers from the same course (**US8**), which is why the tools should provide an evaluation opportunity for peers (**UR6**).

4.3 Deriving of Preliminary Design Principles

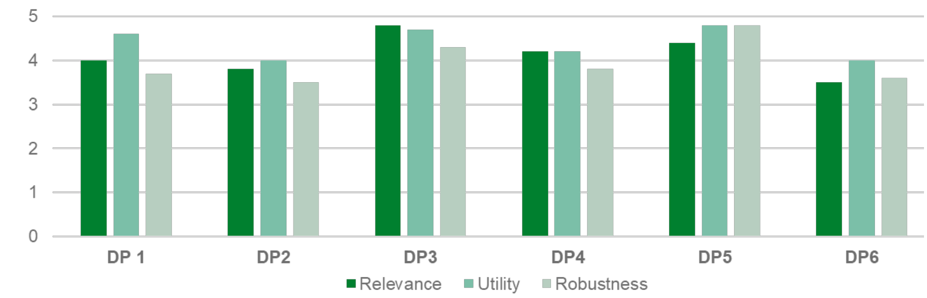
Next, we derived six DP for self-regulated learning tools based on EPM for students to interactively monitor their learning processes, following the DP structure of Gregor et al. (2020) [44].

The first principle (**DP1**) emphasizes the need for an easy to use, intuitive, web-based dashboard within the educational institution's LMS to allow students to easily access and monitor their individual learning path of multiple courses. Learning through different TLM environments can increase cognitive load [50], wherefore it is important to integrate the tool within existing learning applications. Further, the self-monitoring tool increases its value when students can receive the EPM-based monitoring for all their courses. The provided tool should therefore include interfaces that support student's attention management [51]. In **DP2**, we propose to employ an option for students to adaptively adjust the monitoring information and evaluation according to their personal preferences and learning style to enable a self-efficant individual learning experience. Users require a different level of detail to monitor their learning process [18]. An adaption of information during the learning process can be implemented by considering various data types, for instance learning behavior or curricular information [52]. Hence, adapting the granularity of information and feedback to the needs of users can also increase trust [53]. Besides, **DP3** includes the embedding of adaptive small-scaled assessments in the individual learning path of students to provide them with formative feedback on their current learning outcome based on priorly set learning objective. Formative feedback for students is based on a preceding self-assessments and computer-based assessments to improve the students' competences and trigger self-regulated learning processes [54].

DP4 highlights the need to monitor and evaluate the individual learning progress and the administrative and organizational aspects of learning, as they can find it difficult to organize their learning plan effectively [55]. Thus, a self-monitoring tool, which helps students to overview the course organization, enables them to learn in a self-regulated and efficient way. In **DP5**, we advise to visualize the learning progress of the course based on students' prior achievements for them to stay motivated to learn and estimate their workload. A visual representation of students' learning progress can motivate learners and increase the reflection on their own performance [56]. EPM is a suitable technology, because it can help learners visualizing their process [23]. This could be instantiated, i.e., in a monitoring dashboard to track competences, learning progress or detect difficulties [57]. In **DP6**, we propose to provide an option for a social but anonymous comparison of the learning progress of students to enable them to compare themselves with their peers.

4.4 User-based Evaluation of pre-liminary Design Principles

In this section, we describe the evaluation of the initial version of the self-monitoring tools based on EPM. We conducted an ex-ante evaluation with seven potential users according to Venable (2016) [45] with the aim to check whether the DPs are useful for potentials users, refine the DPs and incorporate change requests. The DPs were evaluated by their relevance, usefulness, and robustness. The answers were captured on a 1-to-5 point Likert scale (1: totally disagree, 5: totally agree). An overview of the evaluation results is captures in figure 3. Additionally, we asked open questions, so that participants were able to provide open feedback about their impression regarding the proposed DP. Further, we wanted students to gain ideas on how to improve the DP. The evaluation exposed positive feedback, showing the need for a self-monitoring tool. Participants emphasized that the tool might be *"useful to perceive the own learning progress and reflect on it".* One potential user argued that such a self-monitoring tool allows students to "*fail fast, fail forward, fail early*", so that *"the student is put in the driver's seat of his own learning progress*".



	DP1	DP2	DP3	DP4	DP5	DP6
Mean	4,10	3,76	4,60	4,06	4,66	3,90
SD	0,37	0,21	0,21	0,19	0,18	0,29

Figure 3. Overview of the evaluation results of our design principles

4.5 Revising and Documenting Evaluated Design Knowledge

After the evaluation, we assessed all change requests and implications for the DPs. In the evaluation of DP3, DP4, and DP5 did not receive any change requests and potential users emphasized the importance of those principles. In the case of DP1, DP2 and DP6, we refined their meaning to improve the quality of DPs. One potential user criticized concerning DP1 that we limited the self-monitoring tool by mentioning the word dashboard, because the dashboard is already an instantiation of the DP. Therefore, we exchanged the word "*dashboard*" into "*tool*", as it can be seen in figure 3. Regarding DP2, we received feedback that "*the adaption of the monitoring information seems to be more the "cherry on top" and in a first instance one should focus on completeness of the important information before dealing with customization options*". Thus, we included the criterion of complete monitoring information in the DP2. Moreover, one interviewee augments that DP6 should include the possibility for students to *"share their progress or completion of courses with peers"*. A second change was to make the social comparison not a compulsory principle for self-monitoring tools, but rather make it optional for students. Besides, one additional design principle (DP7) was proposed by several potential users. The self-monitoring tool should also provide personalized nudging and gamification elements based on the monitoring of personal learning paths to motivate students. Students do not only want to monitor their learning path, but also want personalized nudges (e.g., informational, goal setting nudges), recommendations and gamified elements (e.g., awards) to foster their motivation [58, 59].

5 Discussion and Conclusion

In the following, we discuss our contributions through the lens of educational IS. We followed the DSR approach by Hevner (2007) to examine what design requirements must be considered for a self-monitoring tool for students. More precise, there is a lack of user-centered design-principles for monitoring tools, which are based on EPM. Therefore, we discussed three LIs based on 66 scientific research contributions and presented two MRs and seven URs based on 9 user interviews. After an evaluation by seven potential users of the IT-tool, we derived seven DP. We contribute to research by deriving design knowledge for a self-monitoring tool for students and enlighten the importance of self-regulation in TML. EPM-based self-monitoring for students guided by our DPs would improve learning and educating by offering actionable insights to educational providers. Further, we unleash the potential of EPM to monitor students' personal learning paths and provide interventions for students to increase self-efficacy.

Self-monitoring and self-evaluation are becoming more important for students, which use TML environments during their learning processes. Thus, the developed DPs can help educational providers to develop tools for self-regulation and consequently improve students' self-efficacy [33] and learning performance [15]. Our evaluation showed that the design principles are promising for students to use a self-evaluation tool. However, our data analysis exposed that the wanted granularity of monitoring information varies per user. This requirement was confirmed by various researchers (e.g., [16, 44, 45]). For instance, DP6, which proposed a social but anonymous comparison of their learning progress with peers, falls short on our expectations. While certain potential users agreed on the usefulness, some provided low rates. This could be due to the fact, that certain genders require a different degree of competitiveness and comparison during their learning process [60, 61]. Therefore, self-monitoring tools should only provide an option for comparison [62]. Moreover, we examined that EPM provides high potential for self-monitoring tools to evaluate personal learning paths of students. EPM can monitor processes and, for instance reveal insights on the learning progress (useful for DP3) or be beneficial for finding of deviations by comparing learning paths (DP6).

Our research study is not without certain limitations. First, our gathered requirements were only from a specific user group in a specific master course, as well as a specific literature perspective. Including other user groups might have led to different results. Second, extending the evaluation, as well as providing a first instantiation (i.e., in form of a mock-up prototype) for the evaluation would improve the quality of this study and ensure the generalizability of DPs. Also, our research is neglecting an ethical consideration of the use of personal learner data. Future research could therefore shed light on the requirements for EPM based on ethical and legal standards, such as [63].

Future research is vital to engage more in the degree of adaptability of self-monitoring tools for students. We acknowledged different learner strategies from users, which could be variable for differences in monitoring granularity. At the same time, it must be evaluated which features of the IT-tool for monitoring have the highest impact on learning performance and the self-efficacy of students. Further, it requires future research to explore all the possibilities of how EPM can be used for self-monitoring on an individual, instructor, and institutional level. Further, we believe that the true value of our preliminary DPs can only be assessed within a solid implementation of an EPM-based self-monitoring tool and requires a definition of use cases for the IT tool. However, we believe this research study already is an important step to design user-centric monitoring tools for students based on EPM.

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