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# Supporting Self-Reflection and Educators: Towards a Digital Pedometer for Learning

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***Abstract***

*Students often have little insight into their learning effort and progress. This is particularly an issue for learning that occurs outside of digital systems such as working on paper-based exercise sheets. Valuable information about the learning process is neither tracked nor evaluated systematically. This hinders students' self-regulated learning and also educators' abilities to intervene or adapt to student needs. A solution may be to actively involve students in collecting learning data themselves, however, it is still unclear what students need and how to motivate them. This paper provides insights from interviews with students on self-tracking to support their learning progress in non-digital environments. A concept of a digital tool is explored by discussing design principles, key features, and potential benefits of tracking students' learning activities. Two main features were suggested to show progress – time-tracking and self-assessment. Incentives like gamification features are also discussed.*

***Keywords:*** *Self-regulated learning; learning analytics; data collection; offline data.*

## 1. Introduction

In higher education, technology-enhanced learning (TEL) tools such as learning management systems (LMS), audience response or e-assessment systems are used for example to distribute materials, enable scalable learning and provide immediate feedback for students and educators (Strickroth & Bry, 2022). These digital approaches collect learning data during their use (e. g. live quizzes) and often provide insights into the learning process with a focus on the lecture. Lecture complementary activities (e. g. exercise sessions, tutorials) are still delivered face-to-face and not all learning activities are provided in a digital format. Thus, a structured data collection on the learning behavior is rarely done. This is also the case for accompanying tasks to deepen the knowledge from the lecture such as taking notes and working on voluntary homework or exercise sheets. Thus, a significant amount of learning takes place outside of digital environments, leaving e. g. issues with tasks and asynchronous activities during self-study untracked. This information is, however, likely to be helpful for students to gain insight into their learning progress and performance and to improve their self-regulated learning skills. Furthermore, this information can also be highly helpful for educators. However, current data collection and analyses rely on easily capturable data from digital systems.

Methods for simple data collection in "offline" contexts are required, focusing on the students. In such scenarios, students need to actively collect data that is not readily available. Educational technology can close this gap (Strickroth & Bry, 2022). A key challenge, however, is that such a data collection approach heavily relies on students. Hence, the gathering of data needs to be done in a non-intrusive way, consider student interests and provide direct benefits such as (new) insights into their learning progress. Although, various self tracking approaches are available in the context of the quantified self movement using smart phones (Rawassizadeh et al., 2015; Wac, 2018), but these are not tailored to track learning progress in non-digital contexts. Therefore, appropriate tools such as a "pedometer" for learning are missing. This paper aims to explore the requirements for an easy data tracking tool to collect so far untracked data based on students' preferences, and proposes concept ideas for a "pedometer for learning".

The research questions (RQ) are: (RQ1) What information is relevant to students to monitor their own learning experience? (RQ2) What are relevant aspects and incentives for users to motivate regular, active data tracking? (RQ3) How can an easy data collection be implemented?

## 2. Background and Related Research

Self-regulated learning (SRL) involves students to take control over their own learning processes to approach academic tasks in a targeted way. These processes fall into three cyclical phases (forethought, performance, self-reflection), which all benefit from detailed information about students' learning (Zimmerman, 2000). Therefore, data is necessary as well as appropriate instruments to measure SRL strategies (cf. Roth et al., 2016). In higher education, various TEL methods are available such as self-assessment approaches (e. g. quizzes, Alhazbi et al., 2024) or audience response systems (ARS; Mader & Bry, 2019) to collect feedback and provide insights in the learning process. However, specific educational technology is often only used by lecturers in lectures if it is provided by the university (e. g. to provide immediate feedback to the educator) and less often used in exercises and self-study to monitor student learning. Since not all learning activities, such as reading learning material or working on homework sheets, are fully transferable to a digital environment, these activities are not covered by the systems.

In their systematic review, Alhazbi et al. (2024) analyzed empirical studies that use existing online trace data e. g. from an LMS to measure learners' SRL skills. They identified various indicators and categorized them into specific SRL types, such as student engagement, often indicated by time spent online. However, these indicators can unlikely capture the complexity or multi-dimensional nature of the learning process and hardly represent the quality or intensity of learning activities in non-digital contexts. In their paper, Egetenmeier and Strickroth (2024) discussed the inherent limitations of using only digital sources in analytics and proposed ideas to crowdsource the data collection in "offline" environments by using existing technologies. For example, QR codes can bridge isolated systems and different learning settings (e. g. hybrid/ face-to-face, asynchronous/synchronous) with a flexible, low effort approach. However, the authors only provided initial thoughts without a full concept to implement this. To go beyond easily accessible data such as logins or achieved points in digital quizzes, dispositional learning analytics considers different data sources (Tempelaar et al., 2017). For example, students' attitudes, perception or habits by analyzing data from self-report instruments (surveys). However, this approach can be problematic regarding correct interpretation, actionable intervention, or simply missing or incorrect data. To motivate students to participate in data collection, Judel et al. (2021) discussed various ideas, such as the demand for suitable tools that provide helpful insights and feedback. They discussed effective ways to engage students in LA and concluded, that concerns about data protection need to be addressed to build a trustworthy LA environment (cf. Ifenthaler & Schumacher, 2016). Another approach to raise participation is including gamification elements (cf. Deterding et al., 2011), which can make the collection process more enjoyable and boost initial engagement (e. g. in ARS, López-Jiménez et al., 2022). Despite unresolved factors that contribute to the success of gamification, empirical studies suggest the effectiveness of this approach (Sailer & Homner, 2020).

In summary, LA approaches often focus on easily available data which does not cover significant learning activities. Data collection beyond these approaches is challenging and dependent on students' willingness to participate. Hence, research is needed on how to minimize barriers to gathering data, what information are perceived to be helpful by students and what incentives will motivate participation.

## 3. Methodology

A requirement analysis using semi-structured interviews with focus groups was conducted to answer the RQs. The interviews were held during three weeks in summer term 2024 (May to June). Overall, 14 students participated in 4 groups (each with 3–4 people) from different fields of studies at LMU Munich, Germany. The majority of the interviewees (N = 11) were first-year bachelor students from STEM fields, but also second-year master and medicine students participated. All interviews were conducted in person on the campus at places where students meet and study. The interview included questions about desired insights into their learning (progress), possible incentives for self tracking data, and privacy. In addition, a Figma design prototype (see Figure 1) was prepared to facilitate discussion. Figure 1 shows two ideas for data tracking of two different metrics (successful finalization of a working sheet and learning time) and represents a small example of the larger design prototype which also contains e. g. a simple dashboard and various automated hints. The design prototype was shown at the end of the interview (except for the first group). The interviews were qualitatively analyzed using Mayring's (2014) thematic analysis method.

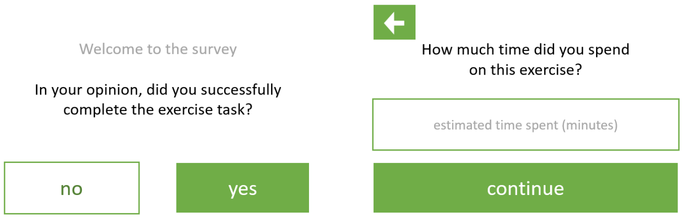


*Figure 1. Two views of the prototype to self-report on performance (left) and learning time (right).*

## 4. Requirement Analysis

This section presents the main results of the interviews. The purpose of the requirement analysis is to gather student perspectives for developing a prototype that collects and monitors currently untracked aspects of learning to foster self-regulated learning. The goal is to find features that are relevant to students for a tool that shows them their learning progress in self-study activities such as working on homework assignments. Most students expressed a strong desire for getting more feedback to evaluate their learning progress and especially their understanding to optimize their learning process. Dashboards with user statistics on learning activities, for example as a weekly review could support them to gain deeper insight into their learning. Voluntary self-assessments or short quizzes were suggested for this purpose, since the results of such tests could indicate what has been understood and what needs further attention. One focus group referred to an existing tool for index cards (Anki) which they use in their language studies. This approach was perceived as simple and understandable to see and track learning progress.

Three groups proposed a timer to track the learning time, e. g. how long does it take to complete a (homework) task. Furthermore, students suggested to combine the time needed with the completeness of the solution to build a useful metric for performance and progress. This may reveal patterns in daily or weekly learning activities that could indicate productive times to increase the learning efficiency. However, doubts were raised about the feasibility of the implementation to capture the performance or understanding of a task, especially when the correct solution is unknown to students.

Another relevant aspect concerns tool usage and motivational factors to engage with a tool. Students suggested general ideas which should be considered to motivate a recurring use of the tool to collect data. On the one hand, these include avoiding barriers to participation, e. g. by providing an easy registration process and access options to the tool, or implementing a "simple" timer to track the time. On the other hand, there was the idea of integrating the tool in lectures or exercises by the teaching staff. For example, a submission feature (for students' homework) could be implemented within the application to encourage regular interaction. Furthermore, the tool could provide access to additional learning material, hints on exercises for students, or dedicated chatbots trained on the course material to answer questions in real-time. students also mentioned time-based gating to prevent gaming-the-system behavior by teasing a later interaction by providing access to solutions or in-depth hints or further tasks. To encourage active participation, two groups suggested gamification elements such as rankings, mini games, level systems or “little rewards” (e. g. animated pictures, learning progress visualizations, badges) as known from commercial applications such as Duolingo. Also, personalized messages such as “we missed you!” after a period of inactivity or positive/encouraging prompts during use were suggested. In general, the interview groups were divided in their opinions about gamified elements and suggested that participation in contests or rankings must be optional. Regarding privacy, most participants preferred anonymity (e. g. using nicknames) and sharing only aggregated data with the teaching staff.

Finally, students provided feedback on the design prototype. Keeping track on the time by entering it manually into a form (cf. Figure 1 on the left) was rated as not feasible, since they often miss to write down exact start and finish times. Instead, they suggested to use an automatic timer. Rating their performance without knowing a correct solution was seen as difficult, especially with only “yes” and “no” as options.

## 5. Concept

Based on the results of the interviews and from related work that inspired the Figma prototype, a tool concept was derived. The tool should supplement existing homework or exercise sessions in an approachable and motivational way, while enabling students to track their own learning. This is made possible by providing simple QR codes that can be integrated directly into learning materials to collect data. An analytics dashboard builds the main feature in the concept that provides students with detailed insights into their learning progress and understanding. Different visualizations of collected data can show information e. g. of a single exercise sheet or in a time-based overview (e. g. weekly, monthly). The time-based view provides insight into study habits, by showing the total number of tasks or sheets the student has worked on, as well as the time spent per day and when. A sheet overview may include charts showing time spent per exercise or the completeness of the task. This should build a basis to estimate the performance or efficiency in different ways. Filtering options in the dashboard could be used to identify difficult tasks, which could serve as a summary for exam preparation.

The collected data should be kept simple and easy to understand. Therefore, the concept focuses on two main aspects of tracking learning progress: First, a timer should be implemented, which automatically tracks time while learning and can be started/stopped for each task individually. Second, different self-assessments tools could be used to evaluate/track understanding and learning progress. For example, predefined multiple-choice questions or quizzes could help to identify strengths and weaknesses in knowledge. Moreover, questions on perceived difficulty, performance, or understanding could be implemented using a simple rating system or an open-ended free text. Numeric ratings can be evaluated easily and combined with the time spent can identify difficult tasks, while free text enables the user to add details that may be helpful when preparing for an exam. This approach is more flexible and less time consuming than comparing students' exercise results to a sample solution by teaching staff.

To encourage recurring and continuous interactions, the tool must provide an additional value for the student. Besides providing a sample solution, additional learning material and targeted hints could support students in their learning task. This may be implemented in form of a simple "help" button to request assistance, hints, or a solution. Another idea includes incorporating gamification elements such as rankings, levels or time-based quests, which could encourage regular learning resp. participation in collecting data. To elevate offline activities with an online support, the tool should be accessible in both contexts. Here, QR codes offer a practical approach, providing a low barrier to start and participate. By scanning a code included on a working sheet access to further material or hints for this specific sheet can be provided. Furthermore, the user can start tracking the learning data. In addition, a simple URL to the tool's website can give independent access to the analytics dashboard. Using the universities' Single Sign-On avoids additional credentials and provides trustworthy authentication.

This concept offers many possible extensions such as providing an interface to the LMS or an existing submission system to simplify processes. Another idea to extend its use could focus on students' self-management and empowerment by setting up data collection for additional sheets by themselves, tracking learning goals or include an extendable configuration of data to collect.

## 6. Discussion, Conclusion and Outlook

This paper presents results from an interview study of freshmen to get ideas, on what information they are interested in, what are incentives for regular use, and how an easy data collection in offline activities of so far untracked data can be implemented. Students showed general interest in visualizing their own learning and understanding. They preferred data collection of easy to understand metrics (e. g., tracking-time and perceived understanding, RQ1). However, students expressed concerns on how to implement this as a tool. In general, low barriers to collect data were requested such as an automatic time tracking and simple (and short) questionnaires on, e. g. self-reported understanding (RQ2). Also, convenience features such as links to the LMS or direct submission was suggested. To incentivize regular use, gamification elements, further hints on tasks, and motivational prompts were suggested (RQ3). However, gamification was seen critically by some students and should therefore be optional.

Particularly, rankings based on time spent or correct answers were named to potentially demotivate students.

Based on these results, a concept for a "learning pedometer" is derived to provide additional insights to students with minimal effort. The concept includes a dashboard showing learning progress, time-tracking features, self-reporting of perceived performance, and (optional) gamification as well as extensions to existing exercise sheets (e. g., assistance to individual tasks, model solutions, and options for submitting a solution) as motivational factors. The concept uses QR codes to link worksheets to the tool so that task specific hints and measurements are possible. This approach empowers students to decide, what data should be included in their personal reports. Since students know what data they provided and the analyses are given to students for self-reflection, there should only be a minimal risk of incorrectly reported information.

The concept is designed to require little effort on the part of students to collect data using an automatic timer and simple self-assessments. A key aspect is to motivate students to participate regularly. Apart from simple gamification approaches, students suggested to provide hints or model solutions. This, however, requires some effort from educators, but may also provide them with more information on the (difficulty of the) tasks which would not be available otherwise. Analytics results for educators should be aggregated to pay attention to privacy concerns of students. The suggested features to include quizzes, index cards or to submit solutions need to be see critically and this may replicate functionality of existing systems and cause additional maintenance costs/effort. A solution may be to rely on SSO and to provide links to an existing LMS, or to integrate the concept such functionality into an existing LMS itself.

Limitations of the study concern the small number of interview partners, which are mainly freshman from bachelors' degree programs in the STEM field from one university in Germany. A saturation of the answers indicates at least that no fundamental different ideas are missing. Furthermore, this concept only covers a small part of student learning activities by focusing on learning time and self-assessments. The paper presents ideas of students on how to track learning in offline learning environments with a focus on self-study in exercises. Further additions such as tracking time of worksheet independent learning (e. g., learning for an exam) need to be considered to better understand individual learning experience and habits. The next step is to implement a fully working prototype based on the concept and evaluate this in an authentic learning environment.

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