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Personalization is no miracle cure: evaluation of a technology-enhanced self-regulated learning intervention for continuing education

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ABSTRACT

Self-regulated learning (SRL) has been considered essential for learning success in continuing education (CE), especially in online learning settings. This paper employs a mixed-methods approach to evaluate a technology-enhanced personalized SRL intervention (TEPSI) that provides a goal-setting functionality, a personalized learning plan, and a personalized dashboard to support SRL in CE. We conducted an experimental study in which participants ($N = 146$) could choose one of three self-paced online learning paths (Agile Management, Data Reporting, or Leadership in Practice) and were asked to complete this learning path within a 12-week learning period. Participants were randomly assigned to an intervention condition, in which the TEPSI was available, and a control condition, in which the TEPSI was not available. The availability of the TEPSI positively affected learners' self-reported time and study environment in the Data Reporting learning path. Still, it did not affect learning processes in the other two learning paths. Further analyses revealed that interacting with the TEPSI could also negatively affect SRL. Moreover, we conducted a qualitative interview study ($N = 20$) using the think-aloud method to gain deeper insights into the benefits and weaknesses of the TEPSI. We identified several issues regarding learners' perceived ease of use and usefulness of the intervention. Our findings show that personalization is no miracle cure and may have negative side effects when not implemented properly. The findings provide several implications for designing TEPSIs for CE.

1. Introduction

Continuing education (CE) is a central element of lifelong learning and is essential for keeping up-to-date in today's rapidly changing society and workforce landscape [1,2]. CE refers to learning activities that are distinct from professional apprenticeships, K-12, and higher education and that aim to develop or renew knowledge, skills, and competences after completing an initial phase of education [3–5]. To successfully participate in CE activities, learners need to engage in self-regulated learning (SRL) to regulate their cognitions, affects, behaviors, and resources [6–8]. For example, learners need to apply SRL strategies to set personal learning goals, manage their study time, monitor their learning progress, and evaluate their learning performance [9,10]. With the increasing popularity of CE activities offered online, the need to engage in SRL has become even greater due to the autonomy and flexibility associated with online learning [6,11].

However, many learners in CE struggle to successfully engage in SRL, which may lead to dropouts and poor learning performance [12–14]. Therefore, researchers have begun to develop interventions to support SRL in CE [15,16]. Recent research has recognized the potential of educational technologies and learning analytics to develop technology-enhanced personalized SRL interventions (TEPSIs). TEPSIs refer to measures employed in digital learning systems that analyze data about learners and their contexts to provide tailored support for SRL. For example, when learners interact in online learning environments, trace data can be analyzed to draw inferences about individual SRL processes and to provide real-time feedback and personalized recommendations to enhance self-regulation [17–19]. However, robust empirical evidence

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regarding the effectiveness of TEPSIs in supporting learning processes in CE is missing. For example, only a few experimental studies have evaluated TEPSIs in the context of CE, and these studies have shown limited effects on learning outcomes and SRL [19–21]. Moreover, studies have shown that learners in CE do not actively engage with TEPSIs [19,22]. For example, in Cobos's [22] study, a monthly average of only 6% of learners in a Massive Open Online Course (MOOC) interacted with a TEPSI that included a personalized dashboard. Thus, further research is needed to design effective TEPSIs for CE and to explore the reasons for these low engagement rates. In addition to further experimental studies evaluating the effectiveness of TEPSIs in supporting learning processes in CE, profound insights into how learners interact with and perceive TEPSIs are needed [23,24]. For example, learners' perceived ease of use and usefulness of TEPSIs should be explored to identify potential benefits and weaknesses from the users' perspective [23,25,26].

This paper employs a mixed-methods approach, collecting quantitative and qualitative evidence to investigate the effectiveness of a TEPSI in supporting learning processes in CE and to explore learners' perceptions of this TEPSI. Such insights may help design effective interventions that learners in CE accept and actively use [23,24,26]. The paper comprises two studies. We first conducted an experimental study (Study 1) to investigate the effects of the TEPSI on learning path completion and learners' self-reported SRL strategies in CE and to explore learners' interactions with the TEPSI. Subsequently, we conducted a qualitative think-aloud interview study (Study 2) to investigate learners' perceived ease of use and usefulness of the TEPSI.

2. Self-Regulated learning in continuing education

SRL describes active and dynamic processes whereby learners monitor and control their cognitive, affective, and behavioral activities during learning to achieve personal learning goals [8,27]. SRL consists of different cyclical phases during which learners engage in SRL strategies to process information resources and regulate internal and external resources [28–31]. While different SRL theories have proposed slightly different conceptualizations of SRL strategies [31–34], Pintrich et al. [31,32] offer a useful framework for categorizing them as cognitive, metacognitive, or resource management strategies. Cognitive strategies (e.g., rehearsal, elaboration) aim at processing information from learning materials [31–33,35]. Metacognitive strategies (e.g., goal setting and planning, self-monitoring) help learners plan, monitor, and control their cognitions and application of cognitive strategies [31,32,36]. Resource management strategies (e.g., time and study environment, effort regulation) involve strategies for regulating other internal and external resources besides cognition, such as motivation, time, and the study environment [31,32,35–37].

Although SRL strategies have been considered a critical aspect for learning success in CE [6,7], SRL theories (e.g., [10,27]) typically focus on K-12 and higher education and neglect the unique nature of SRL in CE [38,39]. Compared to learners in K-12 and higher education, learners in CE usually have to balance learning with more concurrent commitments (e.g., work, family), which may limit their available learning time and lead to distractions. While learning is the main occupation of K-12 and full-time higher education students, CE usually occurs alongside learners' main occupation (e.g., work) and may be less prioritized than concurrent commitments [13,19,40]. Moreover, learners in CE are usually characterized by a stronger need for self-direction than learners in K-12 and higher education [41–43] and are often given a higher degree of autonomy to decide when, how, and what they would like to learn [44]. Therefore, the factors that trigger learners' use of SRL strategies and the relevance of specific SRL strategies differ between CE and K-12 as well as higher education [6].

According to Hemmler and Ifenthaler's [6] systematic review and meta-analysis, SRL in CE is shaped by learning process-related (e.g., lack of time available for learning), learner-related (e.g., prior knowledge), CE-related (e.g., duration), and work-related (e.g., organizational learning culture) factors that may affect learners' use of SRL strategies. Further, Hemmler and Ifenthaler [6] found that metacognitive and resource management strategies were more strongly related to learning performance in CE than cognitive strategies. Metacognitive strategies, such as goal setting, planning, self-monitoring, and self-evaluation, have been considered crucial for regulating learning processes in contexts with a high degree of learner autonomy [19,44]. However, research has shown that learners in CE often have difficulties with engaging in successful metacognitive self-regulation. For example, learners in CE face challenges in setting specific and realistic learning goals [45,46], creating a feasible learning plan [46,47], monitoring their learning progress [46], evaluating their learning performance objectively [46], and adapting their learning behavior to improve performance [46,48]. Furthermore, effective resource management strategies are important for regulating time and motivational resources, organizing a quiet study space, and resisting distractions from conflicting commitments in CE [14,19,32]. In particular, time management has been considered essential for CE due to scheduling conflicts [14,40,49]. In their systematic review and meta-analysis, Hemmler and Ifenthaler [6] identified effective time management as a prerequisite for other SRL strategies in CE, such as cognitive strategies and peer learning, that require time for successful implementation [48,50,51]. Accordingly, lack of time and ineffective time management have been identified as common reasons for dropout from CE [13,14,49,52].

3. Supporting self-regulated learning in continuing education

Since lack of time is a common challenge in CE [13,52], interventions to support SRL in CE should focus on effective time management and be designed to be efficient, requiring minimal additional time beyond learning activities [19,53]. Time-consuming interventions, such as online tutorials teaching SRL strategies or written reflection tasks asking learners to answer specific questions to trigger self-regulation, have not proven beneficial for CE [54–56]. Moreover, researchers have argued that SRL in CE requires personalized support [19,46], as learners in CE are distinguished by their unique life experiences and diverse preconditions [42,57]. For example, learners may enter a CE activity with different expectations, time resources, and levels of prior knowledge, which may impact SRL [6,58,59].

Hence, researchers have employed educational technologies to develop TEPSIs for CE, such as personalized dashboards (e.g., [21,22,60]), personalized prompts [21,53], and personalized recommendations of learning content [19,61], learning times [19], and learning partners [62]. For example, Cobos [22] and Pérez-Álvarez et al. [60] developed personalized dashboards to support SRL in MOOCs by providing visualizations of individual learning behavior and comparisons with other learners. Further, Psathas et al. [21] developed a personalized dashboard to support SRL during collaborative learning activities in a MOOC, along with personalized e-mail prompts to encourage learners to use the dashboard. Teich et al. [19] introduced a TEPSI for a work-related online course to help learners manage their time, attention, effort, and study environment. The TEPSI consisted of a structured course overview, including personalized estimations of the learning time needed to complete the content modules of the course and personalized highlighting of recommended learning content based on learners' prior knowledge. Moreover, Khiat [53] introduced a TEPSI to support learners' time management in an online course for healthcare professionals. The TEPSI comprised a recommended study schedule and adaptive release of learning materials, which allowed learners to access new topics only after completing the prerequisites, as well as personalized e-mail prompts with feedback on time management and learning progress. Unlike online tutorials (e.g., [54]) and written reflection tasks (e.g., [55]), TEPSIs may provide tailored support during the individual learning process and require less time and effort in addition to learning activities [19,46].

Nevertheless, although researchers have emphasized the potential of

TEPSIs [46,63,64], their effects tend to be less promising than expected. In systematic reviews summarizing research on TEPSIs in different learning contexts (e.g., K-12 education, higher education, CE), only a minority of the included studies reported positive effects of TEPSIs on learning outcomes and SRL, and robust experimental studies are scarce [17,18,64,65]. Especially for the context of CE, only a few studies have employed control group designs to experimentally evaluate the effectiveness of TEPSIs in supporting learning processes, and the empirical evidence from these studies is limited [19–21,53]. For example, the introduced TEPSIs showed negligible effects on SRL (e.g., [21]), addressed only isolated SRL strategies (e.g., [53]), were not actively used by learners (e.g., [19]), or the studies were subject to methodological limitations, such as no random assignment of learners to intervention and control conditions, limiting causal conclusions (e.g., [53]). Moreover, experimental studies on TEPSIs in CE have examined only one CE activity [19,21,53]. Researchers have argued that SRL is shaped by contextual characteristics, such as the characteristics of the learning activity [6,28,59]. For example, SRL strategies have been considered more important the longer the duration of the learning activity [6]. Further, specific learning content may require specific SRL strategies [6,66]. Therefore, further experimental studies are needed to evaluate the effects of TEPSIs on learning outcomes and SRL in CE and to compare the effects of TEPSIs across different CE activities.

Moreover, to address the limited impact of existing TEPSIs and learners' limited engagement with them, robust insights into how learners interact with specific TEPSI features are needed. Understanding how learners in CE engage in SRL and how they use TEPSIs to support their learning processes can help identify common learner challenges and support needs [24,67]. In addition, insights into learners' perceptions of the ease of use and usefulness of TEPSIs can help identify the barriers and enablers to engaging with such interventions [25,68,69]. Perceived ease of use refers to the degree to which a person believes that the handling of a system is easy and free of effort [25,68,70]. Perceived usefulness refers to a person's evaluation of the utility of a system for enhancing performance within a particular context of use [68,71,72]. Both perceived ease of use and perceived usefulness have been considered important predictors of learners' intention to use and engage with pedagogical interventions [25,69,73]. However, comprehensive studies investigating learners' perceived ease of use and usefulness of TEPSIs in CE are missing.

4. The technology-enhanced personalized self-regulated learning intervention of the edyoucated-platform

4.1. The edyoucated-platform

We evaluated the TEPSI of the edyoucated-platform (https://edyoucated.org/). The edyoucated-platform, described in detail by Rasch and Middelbeck [74], is an online learning platform for CE that offers learning paths on a broad variety of topics (e.g., Learning and Development Technology, Data Reporting). A learning path on the edyoucated-platform consists of an ordered collection of learning materials (e.g., videos, texts, quizzes) that are grouped into different learning units called skill atoms (see Fig. 1).

One key function of the edyoucated-platform is its ability to personalize a learning path based on individual learners' prior knowledge. The central idea is to let learners skip the skill atoms of a learning path that they have already mastered based on their individual level of prior knowledge. Thus, the number of skill atoms and related learning materials decreases as prior knowledge increases, and the learning path becomes shorter. The basis of this learning path personalization system is the assessment of learners' prior knowledge, which is done through multiple assessment elements that are integrated into the learning path (see Fig. 2). For a more detailed description of the edyoucated-platform and its learning path personalization system, we refer to the prior work of Rasch and Middelbeck [74] and Fromm et al. [75].

Personalized learning, as implemented by the learning path personalization system of the edyoucated-platform has been considered beneficial for providing tailored learning experiences in CE. Due to the growing heterogeneity of learners in CE (e.g., in terms of expectations and prior knowledge), researchers have advocated for personalized learning opportunities, not only to support SRL but also to provide flexible CE activities tailored to the needs of the individual learner [58,76]. A recent study revealed positive effects of the learning path personalization system of the edyoucated-platform on knowledge increase in CE [75]. However, continuous adaptation and personalization of learning processes may also create complexity, which makes it difficult for learners to orient themselves within the learning environment and to self-regulate their learning processes [77,78]. Thus, personalization not only creates opportunities for providing personalized support for SRL but also enhances the need for effective SRL strategies. Therefore, this paper introduces a TEPSI that is integrated into the learning path personalization system of the edyoucated-platform and aims to help learners self-regulate their learning processes while completing

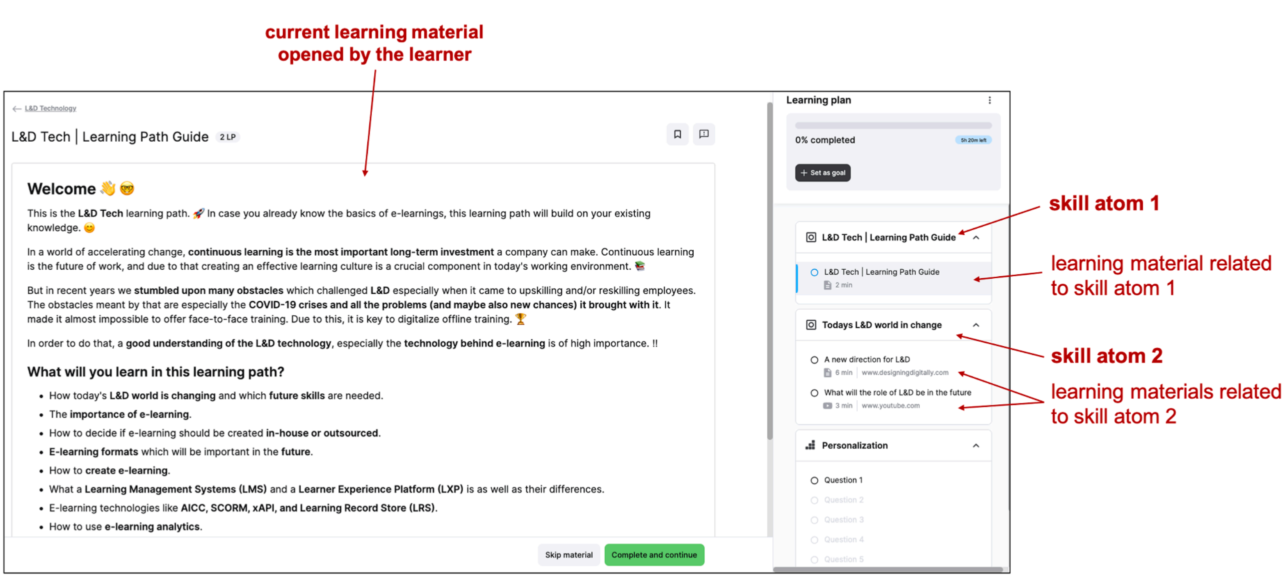

Fig. 1. Overview of the Learning and Development (L&D) Technology Learning Path.

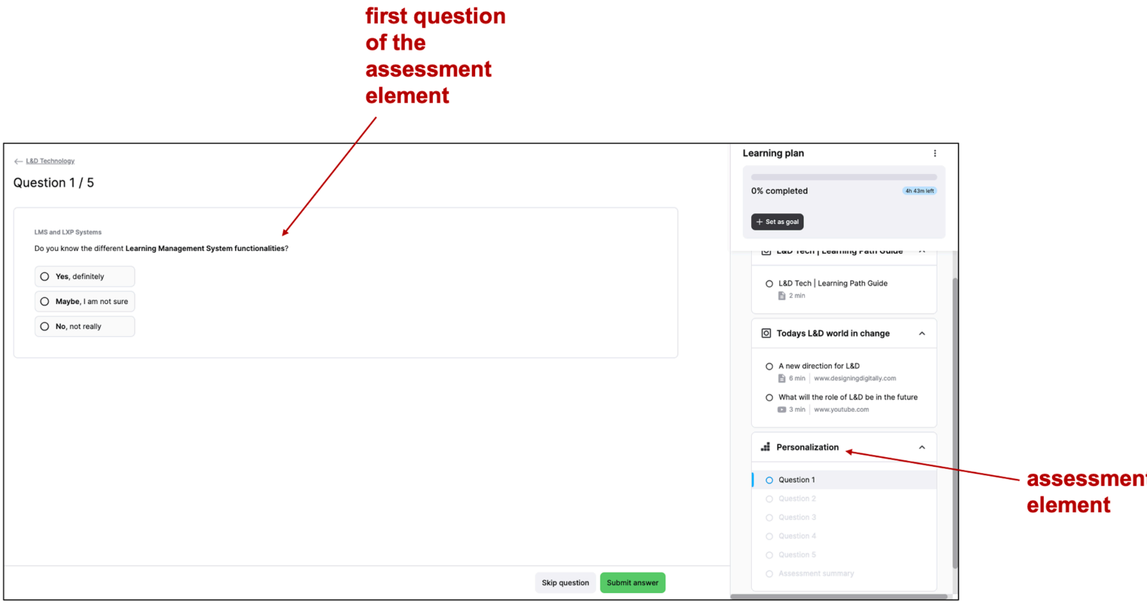

Fig. 2. Assessment Element Within the Learning and Development (L&D) Technology Learning Path.
Note. To allow learners to start their learning process as quickly as possible, learners' prior knowledge is assessed incrementally. That is, instead of asking all assessment questions at the beginning of the learning path, the assessment is typically started with one assessment element at the beginning of the learning path and then continuously mixed into the path. Thus, different assessment elements, each containing up to five questions that measure learners' prior knowledge regarding the subsequent learning content, are alternated with learning materials. The assessment can either be done through self-report or knowledge questions. However, for the studies presented in this paper, only assessments through self-report questions, as presented in this figure, were used.

personalized learning paths.

4.2. The intervention

The TEPSI developed for the edyoucated-platform is based on the challenges and implications that have emerged from recent research focusing on SRL in CE (e.g., [6,46]). It provides continuous monitoring and guidance based on factors that have been identified as relevant to SRL in CE, such as available learning time and learning duration [6]. Moreover, since the importance of metacognitive and resource management strategies has been emphasized for CE [6,19,79] and since learners in CE tend to struggle with these strategies [46,47], the TEPSI of the edyoucated-platform focuses on supporting metacognitive and resource management strategies. Nguyen et al. [46] conducted an interview study to identify desirable features for SRL interventions in CE. According to their findings, metacognitive strategies may be supported by assisting learners in setting learning goals and creating a learning plan, by providing visualizations that enable learners to track their progress toward those goals, and by offering recommendations for improving learning behavior. Further, according to Nguyen et al. [46], resource management strategies may be supported by providing information on required learning time, by breaking down overall learning goals into smaller goals, and by providing personalized motivational messages. These desired features were integrated into the TEPSI of the edyoucated-platform.

The TEPSI of the edyoucated-platform consists of a goal-setting functionality, a personalized learning plan with weekly learning time recommendations, and a personalized dashboard that visualizes the personalized learning plan. The goal-setting functionality can be found both on the starting page of the edyoucated-platform and in the overview of a specific learning path (see Fig. 3). When learners click on the "Set a goal"/"Set as goal"-button, they can specify an overall learning goal consisting of the learning path they would like to complete and a deadline by which they would like to have this learning path completed. Learners can choose the deadline individually based on their available learning time. To help learners set a realistic overall learning goal, an estimation of the average weekly learning time required to complete the learning path until the deadline is displayed when learners select a specific date (see Fig. 4). Learning materials on the edyoucated-platform are assigned a learning duration in minutes, which is based on an expert estimation and empirical data from previous learners who have completed the learning material. The average weekly learning time displayed when learners select a date is calculated based on the remaining weeks until the selected date and the sum of the duration of all remaining learning materials in the learning path that the learner still needs to complete (i.e., all learning materials that the learner has not yet completed and that cannot be skipped due to prior knowledge).

When the overall learning goal is set, a personalized learning plan with weekly learning time recommendations in the form of weekly goals is generated. The learning plan breaks down the overall learning goal into weekly goals consisting of a time commitment in minutes that the learner has to invest each week to finish the learning path until the self-set deadline. Based on the learning duration assigned to each learning material, the learning plan distributes the learning materials along the learning path evenly over the remaining weeks until the deadline. Based on individual learning behavior, the weekly goals are adjusted continuously: If a learner has not achieved a weekly goal and needs to catch up, the goals for the upcoming weeks until the deadline are increased. Conversely, if a learner completes more learning materials than planned in the current week's goal, the goals for the upcoming weeks are reduced. Moreover, if a learner completes an assessment element of the learning path personalization system and is allowed to skip specific skill atoms due to prior knowledge, the weekly goals are reduced. Thus, the weekly goals are not fixed requirements but rather serve as adaptive guidance for learners, providing recommendations to improve their planning and time management.

In the learning path overview, learners can open a personalized dashboard to access their personalized learning plan and monitor their individual goal progress (see Fig. 5). The personalized dashboard consists of three parts: overall progress, weekly goal, and details. Fig. 6 shows different possible states of the personalized dashboard. The overall progress part visualizes learners' progress toward their overall learning goal. It provides personalized feedback, including a timely progress indicator (on track, at risk, overdue, or completed) and a short,

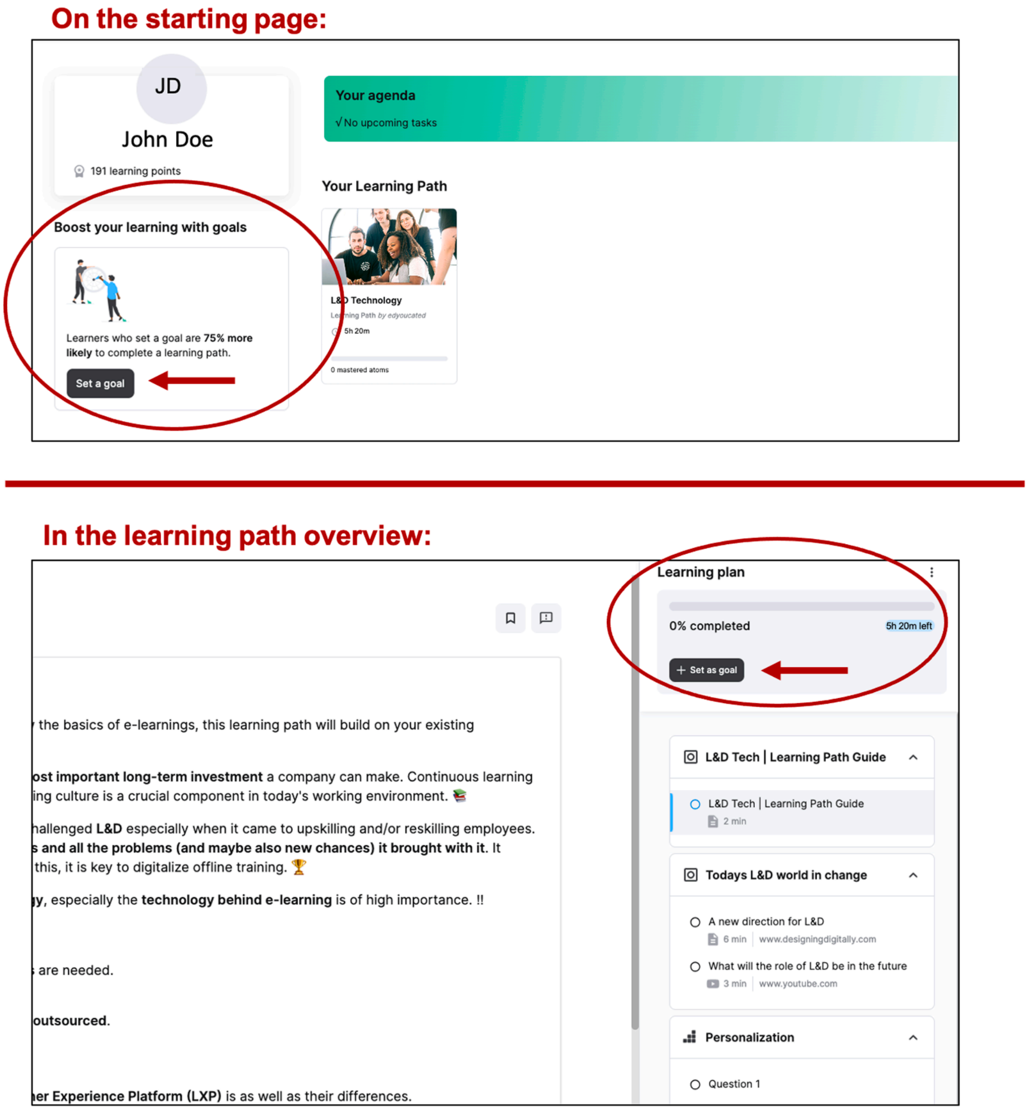

Fig. 3. Accessing the Goal-Setting Functionality.

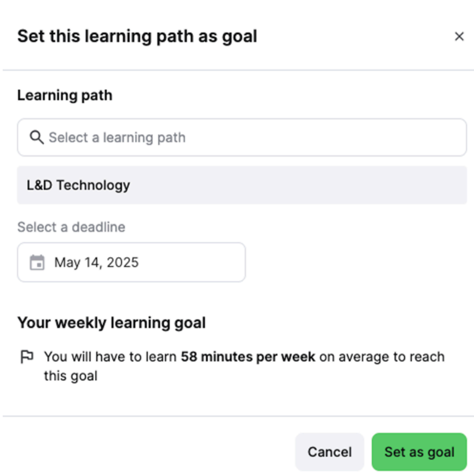

Fig. 4. Setting an Overall Learning Goal.

text-based motivational message. The timely progress indicator is calculated based on the learner's overall progress in the learning path since the start of the learning goal, compared to the progress the learner should have made when learning consistently until the deadline.

The weekly goal part of the dashboard displays the previous week's, the current week's, and the following week's goal. Moreover, learners can see whether they achieved the previous week's goal and track their progress toward the current week's goal. Since the weekly goals are based on the duration assigned to the learning materials, and since the duration of different learning materials within a learning path vary, the weekly goals may differ between the weeks and fluctuate around the average weekly learning time. Moreover, in the TEPSI, a week is defined as starting on Monday and ending on Sunday. Thus, if the overall learning goal is set on a day other than Monday, the first week's goal may be lower compared to the remaining weeks.

Finally, in the details part, learners can see a more detailed description of their progress within the learning path. Moreover, learners can abandon their overall learning goal (which leads to deleting the generated learning plan) or update their overall learning goal by setting a new deadline (which leads to recalculating the weekly goals). As such, learners remain in control of their learning process and can adjust their learning plan at any time if their time constraints change. Table 1 provides a detailed overview of how the TEPSI of the edyoucated-platform addresses specific SRL strategies.

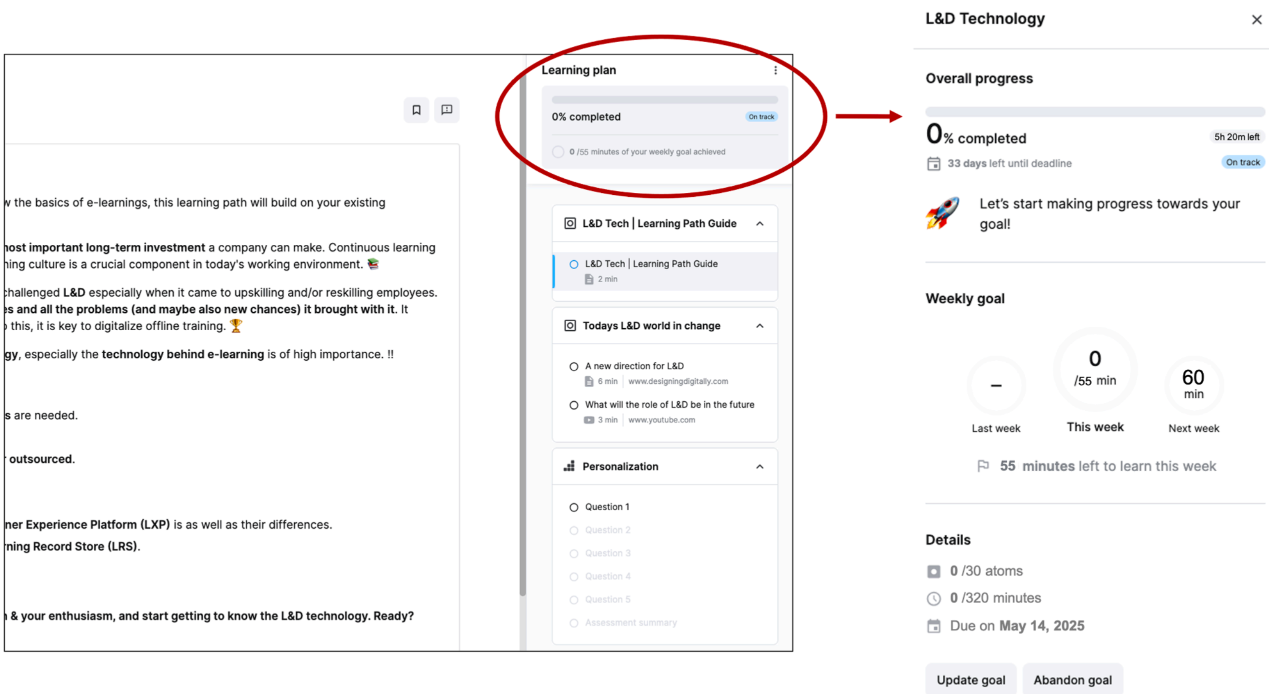

Fig. 5. Accessing the Personalized Dashboard.
Note. The figure shows the learning path overview after setting an overall learning goal. By clicking the grey widget in the top-right corner, learners can open the personalized dashboard.

5. Research questions

This paper addresses the three research gaps discussed in Section 3: (a) the lack of effective TEPSIs for the context of CE, (b) the lack of experimental studies evaluating the effectiveness of TEPSIs in supporting learning processes in CE, and (c) the lack of insights into learners' interactions with and perceptions of TEPSIs in CE to identify enablers and barriers to learners' engagement with such interventions. By collecting comprehensive quantitative and qualitative data to evaluate the TEPSI of the edyoucated-platform, which is based on recent research on SRL in CE (see Section 4.2), this paper aims to inform the design of effective and user-centered TEPSIs for CE. To this end, the experimental study (Study 1) and the interview study (Study 2) conducted for this paper address the following research questions:

1. How does the availability of the TEPSI affect learning path completion and learners' self-reported SRL strategies in CE? (Study 1, Research Gap a and Research Gap b)
2. How do learners' interactions with the TEPSI affect learning path completion and self-reported SRL strategies in CE? (Study 1, Research Gap a and Research Gap c)
3. How do learners in CE evaluate the ease of use of the TEPSI? (Study 2, Research Gap a and Research Gap c)
4. How do learners in CE evaluate the usefulness of the TEPSI for supporting SRL? (Study 2, Research Gap a and Research Gap c)

To answer Research Questions 1, 2, and 4, we specifically focused on the SRL strategies addressed by the TEPSI of the edyoucated-platform (see Table 1). Since SRL may be shaped by characteristics of the learning activity [6,28,59], Study 1 investigated the effects of the TEPSI across three different learning paths (Agile Management, Data Reporting, Leadership in Practice).

6. Study 1

6.1. Method

6.1.1. Research design and procedure

We conducted an experimental study with a between-subjects design. Participants were randomly assigned to one of two experimental conditions: (1) the intervention condition, in which the TEPSI described in Section 4.2 was activated, or (2) the control condition, in which the TEPSI was not activated. In both conditions, participants could choose one of three learning paths of the edyoucated-platform: Agile Management (total learning duration of approximately 5.5 h), Data Reporting (approximately 6.5 h), or Leadership in Practice (approximately 10 h). These three learning paths were selected because they differed in both duration and topic, which allowed for an exploratory investigation into how contextual characteristics might influence the effects of the TEPSI. Moreover, we assumed that offering a variety of learning paths would attract more participants and thus facilitate recruitment. All three learning paths included learning materials in the form of videos, texts, and short quizzes. The learning materials of the Agile Management learning path covered the basics of agility in project and product management, as well as methods for planning and implementing agile processes. The Data Reporting learning path focused on the general principles of data visualization, storytelling, and design thinking, as well as common data pitfalls. The Leadership in Practice learning path covered strategic and agile management methods, data analysis principles, effective communication and feedback, as well as the basics of change and diversity management. A detailed overview of the learning paths is presented in the Supplementary Material S1. Participants were given a period of 12 weeks to complete their chosen learning path. Within this period, learning was self-paced.

The study was conducted entirely online. An overview of the study procedure is presented in Fig. 7. Participants were asked to complete a pre-questionnaire to provide information on their demographics and perceived SRL strategies. The pre-questionnaire also included an instruction video (approximately 3 min) whose content differed across the

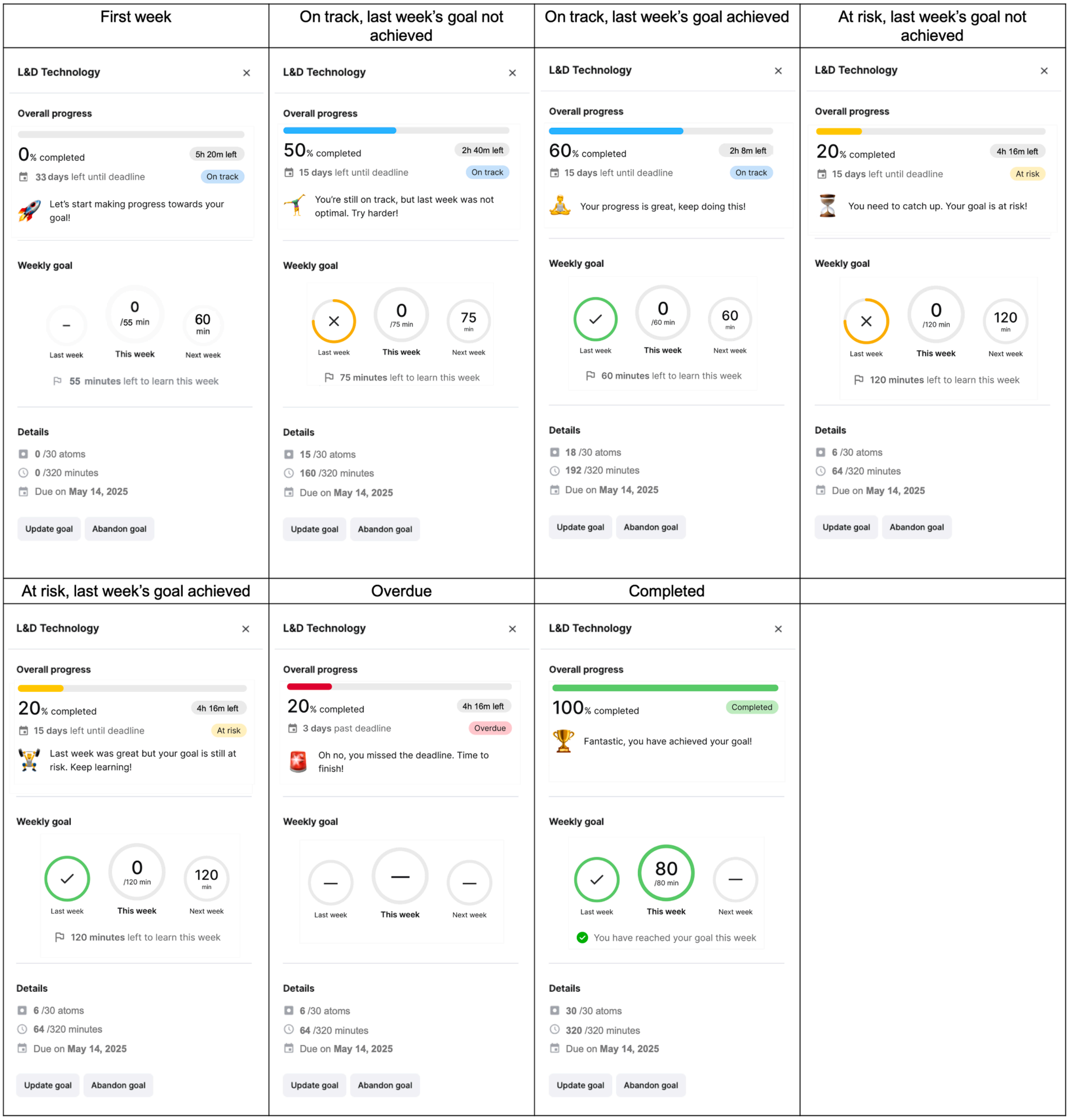

Fig. 6. Possible States of the Personalized Dashboard.

two experimental conditions. The instruction video for the intervention condition included a detailed explanation of the TEPSI of the edyoucated-platform. Participants were asked to use the TEPSI during their learning process and to set an overall learning goal consisting of their chosen learning path (Agile Management, Data Reporting, or Leadership in Practice) and a deadline within the 12-week learning period. The TEPSI was not mentioned in the control condition's instruction video. Instead, participants were instructed to complete their learning path within the 12-week learning period and were provided with a detailed explanation on how to register on the edyoucated-platform.

Once participants had completed the pre-questionnaire, they were provided with a link leading to their learning path on the edyoucated-platform. Participants could only access the learning path for which they registered and not the other learning paths of the platform. The learning paths were identical across the two experimental conditions. However, only participants in the intervention condition could use and interact with the TEPSI. As a placeholder, instead of the TEPSI, participants in the control condition could specify a weekly learning time as a learning goal and monitor their goal progress on the starting page of the platform (see Fig. 8). In contrast to the weekly goals in the intervention condition, the learning goal in the control condition was fixed and did not change based on individual learning behavior. When learners in the control condition clicked on the grey widget in the learning path overview, they were presented with a dashboard showing their overall progress in the learning path, but no specific personalized feedback and no weekly goals (see Fig. 9). These features provided in the control condition refer to typical features of online learning platforms, such as

Table 1
Self-Regulated Learning Strategies Addressed by the Intervention.

SRL strategy	Definition	How the intervention aims to support the strategy
Metacognitive strategies		
Goal setting and planning	Thinking about what needs to be learned, setting learning goals, and building a plan to approach these goals [34,36]	• Encourages learners to set an overall learning goal • Helps set realistic goals through the calculation of the average weekly learning time • Creates a personalized learning plan with weekly goals
Self-monitoring	Self-observing the current learning progress, knowledge, or comprehension of the learning content [36]	• Provides a dashboard to track overall and weekly goal progress
Self-evaluation and reaction	Reflecting and assessing one's learning performance in relation to learning goals and adjusting one's learning behavior for future learning sessions [31,32, 36]	• Encourages evaluation and regulation of learning behavior through personalized feedback provided in the dashboard • Provides recommendations to improve learning behavior by adapting weekly goals to individual learning behavior • Provides the possibility to update the overall learning goal if it has become unreachable
Resource management strategies		
Time and study environment	Scheduling and managing one's learning time as well as organizing a quiet study environment that is free of distractions [31,32]	• Calculates and adjusts the weekly learning time that is necessary to achieve the overall learning goal • Helps learners schedule their learning time in a quiet study environment through anticipatory calculation of weekly learning time commitments
Effort regulation	Controlling motivation and effort to persist even when faced with difficulties, distractions, or uninteresting tasks [31,32]	• Regulates motivation and effort by breaking the overall learning goal into smaller weekly goals • Provides personalized feedback containing a motivational message and visualizes individual goal progress to enhance motivation

Note. SRL = self-regulated learning.

edX (https://www.edx.org/) and Udemy (https://www.udemy.com/), and, therefore, provide a realistic baseline for comparison with the TEPSI.

Participants could log in to the platform and access the learning path as often as they wanted within the 12-week learning period. Once participants had completed all learning materials of their learning path or the 12-week learning period had passed, they were provided with a link to a post-questionnaire in which they were again asked to self-report their SRL strategies. All participants were asked to complete the post-questionnaire, regardless of how far they had progressed in their learning path.

6.1.2. *Participants*

Participants were recruited via social media channels, the network of three employer associations, and the research team's personal and professional contacts. The target group for recruitment was adults interested in continuing education. Therefore, all adults (i.e., at least 18 years old) interested in completing one of the three learning paths could participate in the study. A total of 162 participants agreed to the privacy and data protection statement and fully completed the pre-questionnaire. However, 15 participants were excluded from the analyses because they did not complete any learning material on the edyoucated-platform. Moreover, one participant was excluded due to technical problems. Thus, the sample used for data analyses included $N = 146$ participants. The majority of participants (87%) were employees. Participants' demographics are presented in Table 2. Out of the 146 participants, 92 completed the post-questionnaire. We included all participants without missing values on the relevant variables in each of the conducted analyses. Consequently, the sample size for analyses including information from the post-questionnaire was smaller than for analyses that did not include information from the post-questionnaire.

6.1.3. *Measures*

Learning Path Completion. Learning path completion was calculated by dividing the sum of completed learning materials by the total number of learning materials the individual participant had to complete (i.e., the learning materials that the participant was not allowed to skip due to prior knowledge). Video and text materials were considered completed once participants clicked on the "Complete and continue" button (see Fig. 1). Quizzes were considered completed once they were answered correctly (participants were prompted to retake quizzes if they were not answered correctly).

Self-Reported SRL Strategies. The SRL strategies presented in Table 1 were assessed using items adapted from the Motivated Strategies for Learning Questionnaire (MSLQ; [31,32]). The items were slightly adjusted to suit the learning environment on the edyoucated-platform (e.g., statements regarding class attendance and exam preparation were changed to statements regarding time spent studying and reviewing learning materials, since the CE activity on the edyoucated-platform did not require physical attendance or specific preparation for exams). Items were assessed on a 7-point Likert scale (1 = fully disagree, 7 = fully agree). The metacognitive strategies addressed by the TEPSI (i.e., goal setting and planning, self-monitoring, self-evaluation and reaction) were assessed in a composite score using the metacognitive self-regulation subscale of the MSLQ. This subscale consisted of 12 items (e.g., "When I study, I set goals for myself in order to direct my activities in each study period", Cronbach's $\alpha_{pre-questionnaire} = .80$, Cronbach's $\alpha_{post-questionnaire} = .85$). Time and study environment was assessed with eight items (e.g., "I make good use of my study time", Cronbach's $\alpha_{pre-questionnaire} = .80$, Cronbach's $\alpha_{post-questionnaire} = .80$). Effort regulation was assessed with four items (e.g., "I work hard to do well even if I don't like what we are doing"). However, due to unsatisfactory

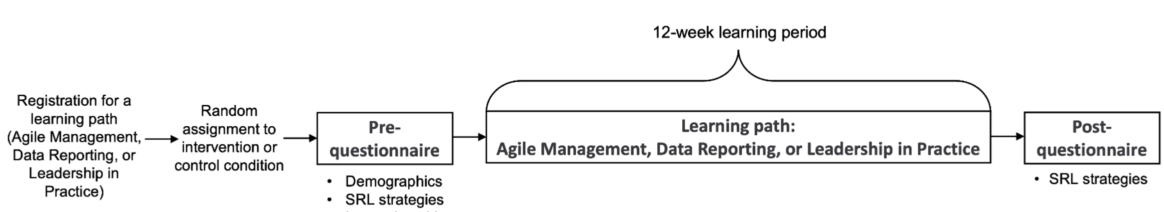

Fig. 7. Overview of the Study Procedure (Study 1).

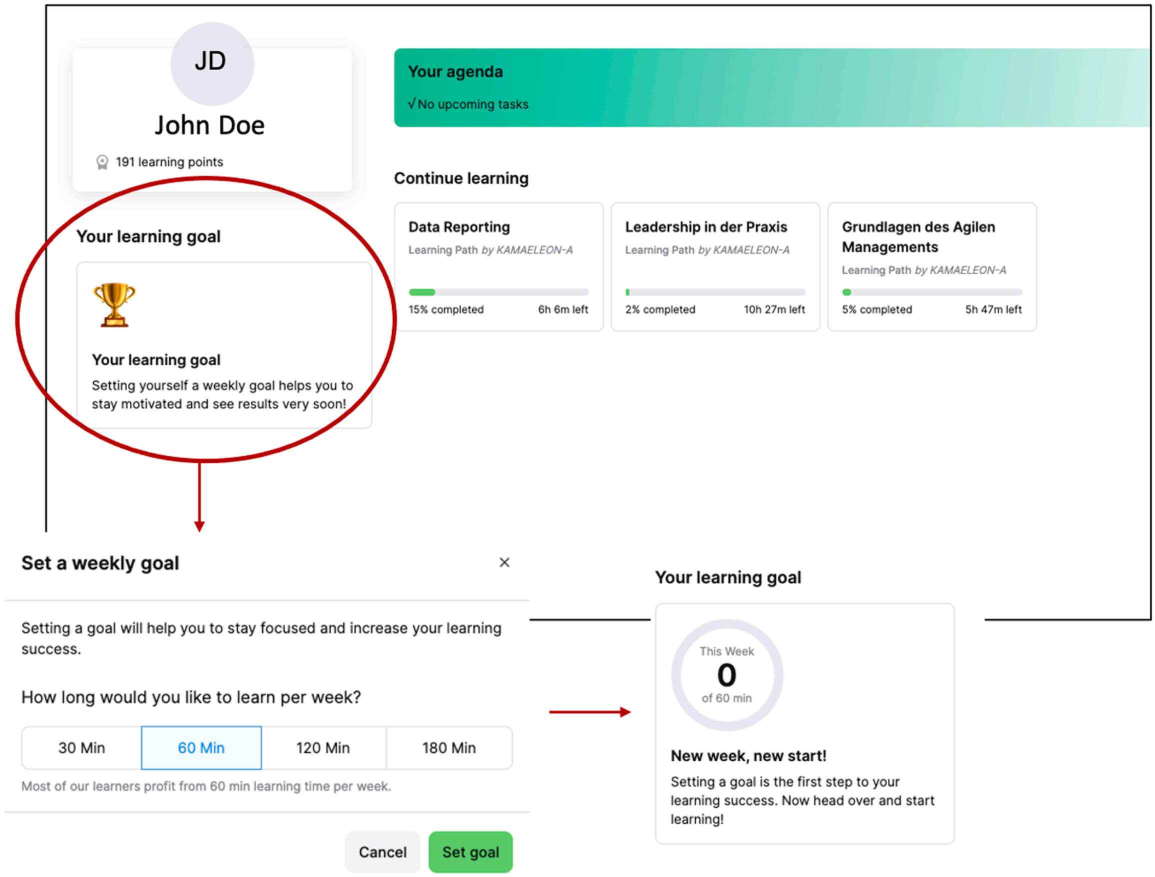

Fig. 8. Goal Setting in the Control Condition (Study 1).
Note. By clicking the widget, learners can set a weekly goal and track their progress on the starting page.

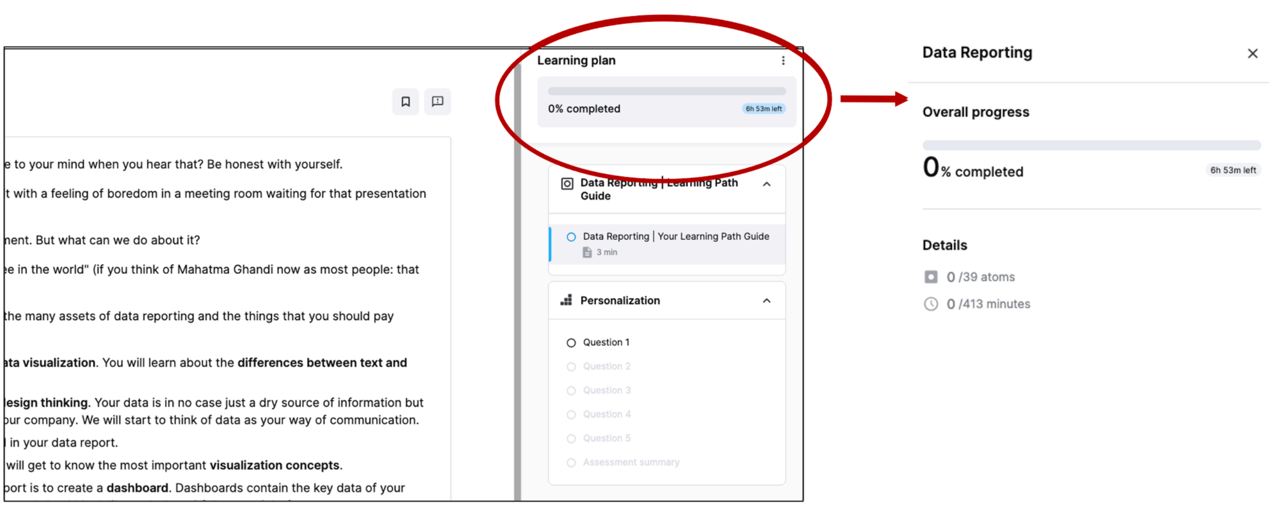

Fig. 9. Dashboard in the Control Condition (Study 1).
Note. By clicking the grey widget in the top-right corner, learners can open the dashboard.

reliability scores (Cronbach's $\alpha_{pre-questionnaire}$ = .68, Cronbach's $\alpha_{post-questionnaire}$ = .51), the effort regulation subscale was excluded from further analyses.

SRL-Related Interactions With the TEPSI. For each participant in the intervention condition, we examined learners' interactions with the TEPSI of the edyoucated-platform. The interaction variables presented in Table 3 were calculated. These variables represent learners' interactions with the core features of the TEPSI, which aim to address the SRL strategies presented in Table 1.

Additional Variables. In addition to the variables specified in our research questions, we examined some exploratory variables for preliminary analyses. For each participant, we calculated the *total number of active days* within the 12-week learning period, that is, the sum of days on which the participant interacted with learning materials in the learning path. Moreover, we determined the *dropout rate* for the three learning paths, that is, the percentage of participants who did not

Table 2
Participants' Demographics by Condition and Learning Path (Study 1).

Variable	Intervention condition (n = 73)			Control condition (n = 73)			Total (N = 146)
	Agile Management (n = 26)	Data Reporting (n = 20)	Leadership in Practice (n = 27)	Agile Management (n = 33)	Data Reporting (n = 17)	Leadership in Practice (n = 23)	
Gender	18 female 7 male 1 divers	11 female 9 male	13 female 14 male	17 female 16 male	10 female 6 male 1 divers	13 female 10 male	82 female 62 male 2 divers
Age	Range: 23–56	Range: 21–56	Range: 24–60	Range: 21–60	Range: 23–62	Range: 21–59	Range: 21–62
	M = 38.31 SD = 10.42	M = 31.85 SD = 9.14	M = 40.19 SD = 11.10	M = 37.33 SD = 9.03	M = 33.76 SD = 10.68	M = 34.91 SD = 10.52	M = 36.49 SD = 10.33

Table 3
Variables Measuring Participants' Interactions with the Intervention (Study 1).

Variable	Description	Specification	Related SRL strategies
Overall learning goal	Describes the participant's usage of the goal-setting functionality	1 = the participant set an overall learning goal consisting of the chosen learning path and a deadline, 0 = the participant did not set an overall learning goal	Goal setting and planning
Sum of dashboard accesses	Describes the participant's usage of the personalized dashboard	Number of times the participant opened the personalized dashboard in the learning path overview (0 if the participant did not set an overall learning goal)	Self-monitoring, self-evaluation and reaction, effort regulation
Sum of goal modifications	Describes the participant's modifications to the personalized learning plan	Number of times the participant modified the deadline of their overall learning goal (0 if the participant did not set an overall learning goal)	Self-evaluation and reaction
Percentage of achieved weekly goals	Describes the participant's adherence to the personalized learning plan with the weekly learning time recommendations	Number of achieved weekly goals divided by the total number of weekly goals (0 if the participant did not set an overall learning goal)	Time and study environment

Note. SRL = self-regulated learning.

complete 100% of the learning materials of their personalized learning path. Further, we calculated the *sum of goal abandonments* for each participant in the intervention condition, that is, the number of times the participant abandoned an overall learning goal. Participants could set and abandon their overall learning goal as often as they wanted, but they could only set one overall learning goal at a time.

6.1.4. Data analysis

Data analyses were performed in R (version 4.3.0). All statistical tests were conducted two-sided. Significance levels were set at .05. To answer Research Question 1, independent-samples t-tests were conducted to determine whether the experimental conditions differed in learning path completion. Moreover, mixed ANOVAs were conducted using self-reported metacognitive self-regulation and time and study environment as dependent variables, time of measurement (pre- vs. post-questionnaire) as within-factor, and the experimental condition as between-factor. Analyses for Research Question 1 were conducted across all learning paths and for each of the three learning paths separately. To answer Research Question 2, learning path completion, as well as self-reported metacognitive self-regulation and time and study environment measured in the post-questionnaire, were regressed on the interaction variables presented in Table 3. For self-reported metacognitive self-regulation and time and study environment, the equivalents of the pre-questionnaire were added as control variables. Due to the limited number of participants in the intervention condition, the multiple linear regression analyses were not conducted for the three learning paths separately.

6.2. Results

6.2.1. Preliminary analyses and descriptive statistics

On average, participants spent $M = 5.21$ ($SD = 4.44$) active days on the edyoucated-platform ($M = 4.71$, $SD = 4.01$ for Agile Management, $M = 6.03$, $SD = 4.72$ for Data Reporting, and $M = 5.18$, $SD = 4.71$ for Leadership in Practice). The dropout rate in all three learning paths was high (66.21%). There was a statistically significant difference in the dropout rate between the three learning paths, $\chi^2(2) = 13.23$, $p = .001$, Cramer's $V = .30$. The dropout rate was higher in the Leadership in Practice (85.71%) than in the Agile Management (59.32%) and the Data Reporting (51.35%) learning paths. In the intervention condition, 86.30% of the participants used the TEPSI to set an overall learning goal (80.77% in the Agile Management, 95.00% in the Data Reporting, and 85.19% in the Leadership in Practice learning path). There was only one participant in the intervention condition who abandoned an overall learning goal. After abandoning the goal, this participant set a new overall learning goal. An overview of descriptive statistics and correlations among variables is presented in the Supplementary Material S2.

Since not all participants completed the post-questionnaire, we conducted exploratory analyses to determine whether participants' baseline SRL strategies measured in the pre-questionnaire influenced their willingness to complete the post-questionnaire. This was done to identify potential biases in the anaylses for self-reported SRL strategies. Self-reported metacognitive self-regulation measured in the pre-questionnaire did not significantly differ between participants who completed the post-questionnaire ($M = 4.92$, $SD = 0.76$) and those who did not complete the post-questionnaire ($M = 4.98$, $SD = 0.97$), $t(91.61) = 0.38$, $p = .706$, $d = 0.07$. Additionally, self-reported time and study environment did not significantly differ between participants who completed the post-questionnaire ($M = 4.65$, $SD = 1.01$) and those who did not complete the post-questionnaire ($M = 4.35$, $SD = 1.04$), $t(144) = -1.68$, $p = .096$, $d = -0.29$.

6.2.2. Research question 1: effects of the availability of the intervention

The results of the t-tests for learning path completion are presented in Table 4. No significant differences were detected between the intervention and the control condition.

The results of the mixed ANOVAs are presented in Table 5 (for means and standard deviations, see Table 6). Significant main effects of time of measurement on self-reported metacognitive self-regulation were detected, indicating that metacognitive self-regulation decreased over time, all learning paths: $t(90) = -4.22$, $p < .001$, $d = -0.44$, Agile Management: $t(34) = -2.27$, $p = .030$, $d = -0.34$, Data Reporting: $t(24)$

Table 4
Results of the t-Tests for Learning Path Completion (Study 1).

Condition	*M*	*SD*	*t(df)*	*p*	*d*	95% CI for *d*
All learning paths ($n = 145$)			**−0.46 (143)**	**.650**	**−0.08**	**[−0.40, 0.25]**
Intervention ($n = 73$)	0.65	0.40				
Control ($n = 72$)	0.68	0.38				
Agile Management ($n = 59$)			**−0.54 (57)**	**.589**	**−0.14**	**[−0.67, 0.38]**
Intervention ($n = 26$)	0.65	0.41				
Control ($n = 33$)	0.71	0.36				
Data Reporting ($n = 37$)			**0.04 (35)**	**.971**	**0.01**	**[−0.66, 0.68]**
Intervention ($n = 20$)	0.74	0.41				
Control ($n = 17$)	0.74	0.38				
Leadership in Practice ($n = 49$)			**−0.13 (47)**	**.894**	**−0.04**	**[−0.62, 0.54]**
Intervention ($n = 27$)	0.59	0.39				
Control ($n = 22$)	0.61	0.41				

Note. Of the sample ($N = 146$), one participant had to be excluded due to technical issues with storing the completed learning materials.

Table 5
Results of the Mixed ANOVAs for Self-Reported Self-Regulated Learning Strategies (Study 1).

Variable	*F*(*df*1, *df*2)	*P*	η^2_{partial}
Metacognitive self-regulation			
All learning paths			
Time of measurement	17.84(1, 90)	< 0.001	.17
Condition	0.02(1, 90)	.895	< 0.01
Time of measurement*condition	0.45(1, 90)	.502	.01
Agile Management			
Time of measurement	5.15(1, 34)	.030	.13
Condition	3.11(1, 34)	.087	.08
Time of measurement*condition	1.50(1, 34)	.230	.04
Data Reporting			
Time of measurement	6.23(1, 24)	.020	.21
Condition	2.85(1, 24)	.104	.11
Time of measurement*condition	1.04(1, 24)	.319	.04
Leadership			
Time of measurement	8.75(1, 28)	.006	.24
Condition	0.10(1, 28)	.750	< 0.01
Time of measurement*condition	0.19(1, 28)	.663	.01
Time and study environment			
All learning paths			
Time of measurement	1.07(1, 90)	.303	.01
Condition	0.23(1, 90)	.635	< 0.01
Time of measurement*condition	2.95(1, 90)	.089	.03
Agile Management			
Time of measurement	0.82(1, 34)	.373	.02
Condition	0.04(1, 34)	.844	< 0.01
Time of measurement*condition	2.16(1, 34)	.151	.06
Data Reporting			
Time of measurement	2.26(1, 24)	.146	.09
Condition	0.55(1, 24)	.464	.02
Time of measurement*condition	5.08(1, 24)	.034	.18
Leadership			
Time of measurement	0.03(1, 28)	.858	< 0.01
Condition	0.11(1, 28)	.743	< 0.01
Time of measurement*condition	0.05(1, 28)	.827	< 0.01

$= -2.50$, $p = .020$, $d = -0.46$, Leadership in Practice: $t(28) = -2.96$, $p = .006$, $d = -0.56$. No significant main effects of the experimental condition and interaction effects on self-reported metacognitive self-regulation were detected. A significant interaction effect on self-reported time and study environment was detected, but only for the Data Reporting learning path. Post hoc analyses using the Tukey method indicated that in the intervention condition, time and study

Table 6
Descriptive Statistics for Self-Reported Self-Regulated Learning Strategies by Time of Measurement, Condition, and Learning Path (Study 1).

Variable	Condition	
	Intervention	Control
Time of measurement: Pre		
Metacognitive self-regulation		
All learning paths	$M = 4.94$, $SD = 0.74$, $n = 46$	$M = 4.90$, $SD = 0.80$, $n = 46$
Agile Management	$M = 4.76$, $SD = 0.73$, $n = 14$	$M = 4.96$, $SD = 0.79$, $n = 22$
Data Reporting	$M = 4.98$, $SD = 0.72$, $n = 15$	$M = 4.57$, $SD = 1.09$, $n = 11$
Leadership in Practice	$M = 5.05$, $SD = 0.78$, $n = 17$	$M = 5.06$, $SD = 0.44$, $n = 13$
Time and study environment		
All learning paths	$M = 4.59$, $SD = 1.14$, $n = 46$	$M = 4.70$, $SD = 0.88$, $n = 46$
Agile Management	$M = 4.71$, $SD = 1.12$, $n = 14$	$M = 4.93$, $SD = 0.87$, $n = 22$
Data Reporting	$M = 4.58$, $SD = 1.24$, $n = 15$	$M = 4.67$, $SD = 0.84$, $n = 11$
Leadership in Practice	$M = 4.50$, $SD = 1.11$, $n = 17$	$M = 4.34$, $SD = 0.89$, $n = 13$
Time of measurement: Post		
Metacognitive self-regulation		
All learning paths	$M = 4.47$, $SD = 1.07$, $n = 46$	$M = 4.56$, $SD = 0.89$, $n = 46$
Agile Management	$M = 4.15$, $SD = 1.10$, $n = 14$	$M = 4.78$, $SD = 0.81$, $n = 22$
Data Reporting	$M = 4.74$, $SD = 1.04$, $n = 15$	$M = 4.00$, $SD = 0.94$, $n = 11$
Leadership in Practice	$M = 4.50$, $SD = 1.05$, $n = 17$	$M = 4.65$, $SD = 0.83$, $n = 13$
Time and study environment		
All learning paths	$M = 4.91$, $SD = 1.20$, $n = 46$	$M = 4.62$, $SD = 1.09$, $n = 46$
Agile Management	$M = 5.14$, $SD = 0.78$, $n = 14$	$M = 4.82$, $SD = 1.00$, $n = 22$
Data Reporting	$M = 5.27$, $SD = 1.37$, $n = 15$	$M = 4.53$, $SD = 1.13$, $n = 11$
Leadership in Practice	$M = 4.40$, $SD = 1.20$, $n = 17$	$M = 4.35$, $SD = 1.20$, $n = 13$

environment significantly increased over time, $t(24) = 2.89$, $p = .038$, $d = 0.66$, whereas, in the control condition, perceived time and study environment did not significantly differ between the pre- and the post-questionnaire, $t(24) = -0.49$, $p = .960$, $d = -0.19$ (see Fig. 10). No other effects on self-reported time and study environment were significant.

To further examine the differential effects of the TEPSI on self-reported time and study environment, we exploratively explored the differences in participants' interactions with the TEPSI between the three learning paths. As shown in Table 7, participants in the Data Reporting learning path tended to engage more actively with the TEPSI than learners in the other two learning paths. They were more eager to set an overall learning goal and to access the personalized dashboard, and they achieved more weekly goals than participants in the other two learning paths. However, none of the differences in participants' interactions with the TEPSI between the three learning paths were statistically significant (see captions of Table 7), potentially due to low statistical power resulting from the small sample sizes.

6.2.3. *Research question 2: effects of participants' interactions with the intervention*

As shown in Table 8, setting an overall learning goal negatively affected learning path completion and self-reported time and study

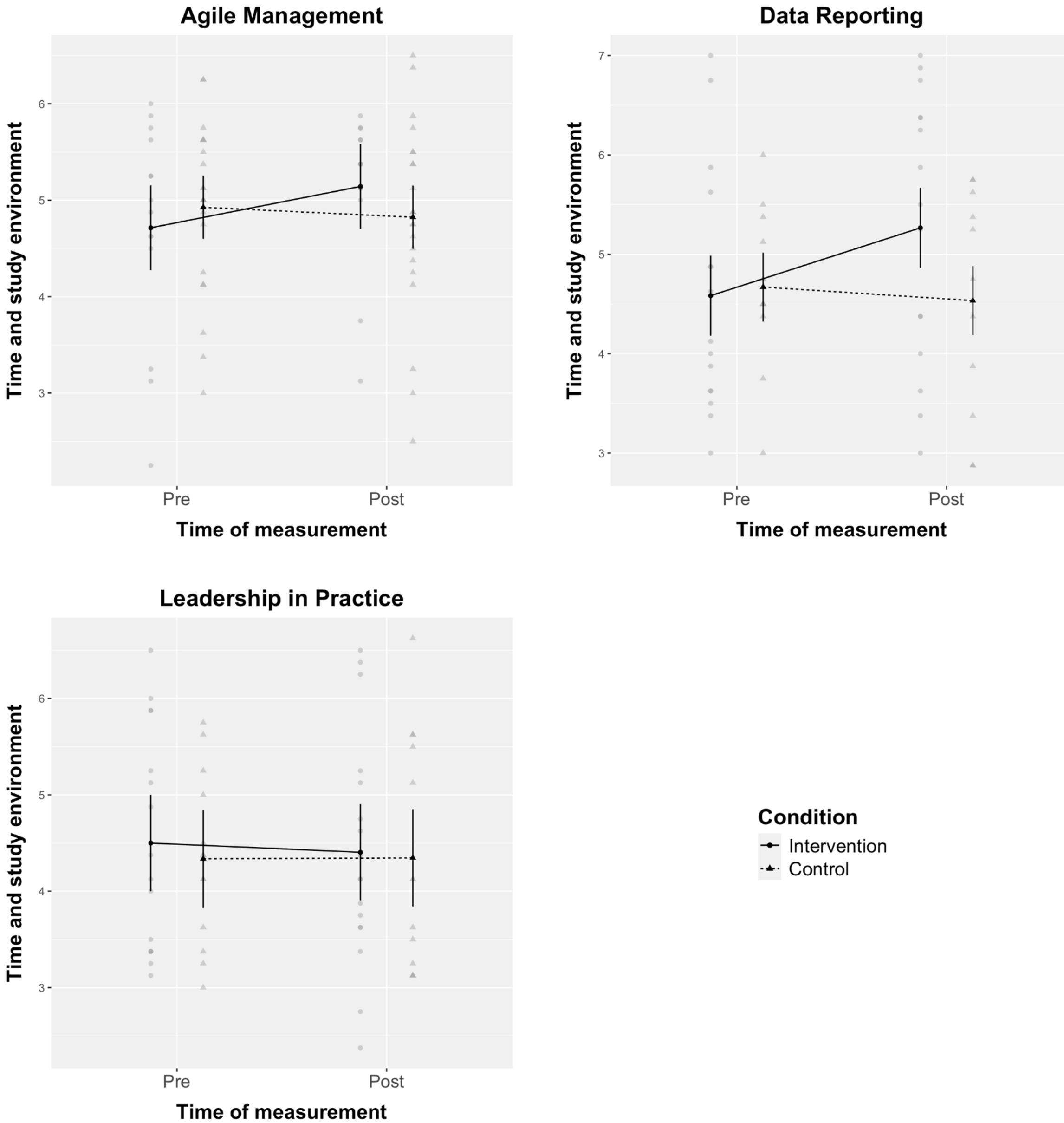

Fig. 10. Interaction Effects on Self-Reported Time and Study Environment Across the Three Learning Paths (Study 1).
Note. Error bars represent within-subject error bars.

environment. On the contrary, the percentage of achieved weekly goals was positively related to learning path completion and to self-reported time and study environment. No other significant effects of learners' interactions with the TEPSI on learning path completion and self-reported SRL strategies were detected.

6.3. Discussion and introduction to study 2

Educational technologies offer potential for providing personalized and timely support for SRL [16,46]. Study 1 evaluated the effects of the TEPSI of the edyoucated-platform on learning path completion and self-reported SRL strategies. In the Data Reporting learning path, the availability of the TEPSI had a positive effect on self-reported time and study environment. However, no other significant effects of the availability of the TEPSI were detected. Further analyses revealed that interacting with the TEPSI may even negatively affect learning path completion and self-reported SRL strategies. Thus, the findings show that TEPSIs may involve both opportunities and risks for SRL [81,82]. To design effective TEPSIs for CE, explanations for these ambivalent findings must be identified. Therefore, in Study 2, learners' perceptions of the ease of use and usefulness of the TEPSI of the edyoucated-platform were investigated to identify potential weaknesses and to explain the positive and negative effects of the intervention.

7. Study 2

7.1. Method

7.1.1. Research design and interview guide

We conducted semi-structured interviews using the think-aloud method. The think-aloud method is a cognitive interviewing technique in which participants are asked to verbalize their thoughts, feelings, and intentions while performing a specific task [83–85]. Such verbalizations may provide detailed information about participants' perceptions and reasoning and have been considered a valuable source for user research [83,86] and for studying individual learning processes [84,87].

For the present study, we developed an interview guide consisting of an introduction part, a main part, and a reflection part. In the

Table 7
Descriptive Statistics of Participants' Interactions With the Intervention (Study 1).

Variable	Learning path			
	All learning paths (n = 73)	Agile Management (n = 26)	Data Reporting (n = 20)	Leadership in Practice (n = 27)
Overall learning goal (relative frequency of participants who set an overall learning goal)	86.30%	80.77%	95.00%	85.19%
Sum of dashboard accesses	M = 1.82, SD = 3.91	M = 1.42, SD = 2.39	M = 3.55, SD = 6.54	M = 0.93, SD = 1.49
Sum of goal modifications	M = 0.18, SD = 0.56	M = 0.08, SD = 0.27	M = 0.30, SD = 0.80	M = 0.19, SD = 0.56
Percentage of achieved weekly goals	M = 0.33, SD = 0.36	M = 0.33, SD = 0.36	M = 0.43, SD = 0.40	M = 0.25, SD = 0.33

Note. No statistically significant differences between learning paths. Fisher's exact test for overall learning goal: $p = .359$, Cramer's $V = 0.16$. Kruskal-Wallis test for sum of dashboard accesses: $H(2) = 4.24$, $p = .120$, $\eta^2 = 0.03$. Kruskal-Wallis test for sum of goal modifications: $H(2) = 0.76$, $p = .685$, $\eta^2 = 0.02$. Kruskal-Wallis test for percentage of achieved weekly goals: $H(2) = 2.01$, $p = .366$, $\eta^2 < 0.01$.

Table 8
Results of Multiple Linear Regression Analyses for Learning Path Completion and Self-Reported Self-Regulated Learning Strategies (Study 1).

Predictor	Regression coefficient				
	B	SE	β	t	p
Learning path completion [a]					
Intercept	0.67	0.14	—	4.73	< 0.001
Overall learning goal (1 = yes, 0 = no)	−0.36	0.15	−.31	−2.34	.022
Sum of dashboard accesses	0.01	0.01	.11	1.39	.169
Sum of goal modifications	0.08	0.13	.11	0.64	.525
Percentage of achieved weekly goals	0.79	0.09	.71	9.03	< 0.001
Metacognitive self-regulation (post) [b]					
Intercept	1.19	1.06	—	1.13	.267
Metacognitive self-regulation (pre)	0.64	0.20	.45	3.19	.003
Overall learning goal (1 = yes, 0 = no)	0.05	0.51	.02	0.11	.915
Sum of dashboard accesses	0.05	0.04	.21	1.18	.244
Sum of goal modifications	−0.06	0.28	−.04	−0.22	.830
Percentage of achieved weekly goals	−0.11	0.48	−.04	−0.23	.822
Time and study environment (post) [c]					
Intercept	3.19	0.55	—	5.83	< 0.001
Time and study environment (pre)	0.38	0.12	.36	3.20	.003
Overall learning goal (1 = yes, 0 = no)	−1.30	0.44	−.37	−2.99	.005
Sum of dashboard accesses	0.03	0.03	.11	0.82	.427
Sum of goal modifications	−0.07	0.24	−.04	−0.30	.769
Percentage of achieved weekly goals	2.26	0.40	.69	5.67	< 0.001

Note. Only participants of the intervention condition were considered.
[a] $F(4, 68) = 25.27$, $p < .001$, $R^2 = 0.52$, $R^2_{\text{adjusted}} = 0.49$. HC3 correction [80] was employed because of heteroscedasticity.
[b] $F(5, 40) = 2.76$, $p = .031$, $R^2 = 0.26$, $R^2_{\text{adjusted}} = 0.16$.
[c] $F(5, 40) = 11.19$, $p < .001$, $R^2 = 0.58$, $R^2_{\text{adjusted}} = 0.53$.

introduction part, participants were informed about the study's purpose and procedure, and demographic information was collected. In the main part, participants were asked to complete specific tasks related to the TEPSI of the edyoucated-platform (e.g., "Please set the learning path 'Learning and Development Technology' as your learning goal") and to think aloud (i.e., to express all their thoughts, feelings, and intentions). A short training was conducted to familiarize participants with the think-aloud method. Then, participants were asked to complete the tasks while navigating on the edyoucated-platform, as well as while being presented with screenshots showing different potential states of the personalized dashboard (see Fig. 6). Finally, in the reflection part, participants were asked to answer different reflective questions regarding their impression of the TEPSI and its potential to support learning processes. An overview of all tasks and reflective questions defined in the interview guide is presented in the Supplementary Material S3. The interviewer was free to ask follow-up questions when clarification was needed.

7.1.2. Participants

Participants were recruited via the research team's personal and professional contacts and had to be adults (i.e., at least 18 years old) to participate in the study. The recruitment for Study 2 was conducted independently of Study 1. The recruitment process was continued until saturation of themes was reached, that is, until additional interviews with new participants no longer yielded any new information relevant to our research questions [88]. A total of $N = 20$ interviews were conducted. The participants (12 female, 8 male) were between 22 and 66 years old ($M = 31.70$, $SD = 8.95$) and employed across different industries (e.g., public administration, pharma, retail).

7.1.3. Data collection

The first six interviews were conducted as part of a master's thesis [89] at the University of Mannheim. The remaining 14 interviews were conducted by the first author of this paper. Participants agreed to the privacy and data protection statement and were provided access to the edyoucated-platform once the interview date was scheduled. Participants were asked to register on the platform and complete at least one learning path of the platform before the interview date so that they would be familiar with the platform's general features. The TEPSI was deactivated for the participants until the interview date so that participants could not interact with the intervention before the interview. The interviews lasted between 27 and 59 min ($M = 35.72$, $SD = 6.69$) and were both audio- and screen-recorded. All interviews were conducted in German. Sample quotations from the interviews presented in this paper (see Section 7.2) were translated into English.

7.1.4. Data analysis

The audio and screen recordings of all interviews were transcribed and analyzed using f4 (https://www.audiotranskription.de/en/). All interviews were coded using deductive and inductive content analysis [90]. To answer Research Question 3, the codes were created inductively based on themes that emerged from the interviews. The codes were developed through repeated reading of the interview transcripts, paraphrasing, and summarizing participants' statements to detect themes related to the participants' perceived ease of use. Similar codes were clustered into three main categories: salience, understandability, and design. The main category salience includes codes for statements describing the degree to which participants perceived the TEPSI and its features as easy to access. Understandability includes codes for statements describing the degree to which the participants perceived the TEPSI and its features as easy to comprehend. The main category design includes codes for statements describing the degree to which participants perceived the design of the TEPSI as clear and appealing. To answer Research Question 4, five deductive main categories (goal setting and planning, self-monitoring, self-evaluation and reaction, time and study environment, and effort regulation) were created based on the SRL strategies addressed by the TEPSI (see Table 1). The codes associated with these main categories were created inductively by repeated reading of the interview transcripts, paraphrasing, and summarizing participants' statements to detect themes related to the specified SRL strategies. Similar themes within one main category were synthesized into one inductive code. The coding manual is available in the Supplementary Material S4.

To develop the coding manual, the first author of this paper conducted a first round of coding based on all interviews. The coding manual was discussed with the research team and updated based on disagreements and misunderstandings that derived from the discussion. Once the final coding manual was set, the first author recoded all interviews. Moreover, a trained research assistant independently coded a random selection of $n = 5$ interviews. Interrater reliability was acceptable (Krippendorff's $\alpha = .77$). Differences between coders were solved by discussion.

7.2. Results

A summary of the findings is presented in Table 9.

7.2.1. Research question 3: perceived ease of use

Salience. Most participants ($n = 15$) noticed the TEPSI on the platform's starting page after logging in. However, in the learning path overview, only nine participants noticed the TEPSI at first glance. When instructed to set an overall learning goal, all participants found the corresponding button. However, four participants had difficulty finding the personalized dashboard and the button to update the deadline.

Understandability. All participants understood the implications of the overall learning goal and the general principles of the dashboard visualizations showing their learning progress. However, some participants had difficulty understanding specific states of the dashboard. For example, five participants were confused that the weekly goals differed for different weeks and did not exactly represent the average weekly learning time displayed when selecting a deadline: "I'm confused because it indicates 30 min. Previously, it said 55 min to make it until May 5" (Interview 17). Two participants were confused because the progress visualized in the dashboard was based on the learning time assigned to the material rather than their actual learning time: "I have already completed 4 out of 40 min, but it did not take me 4 min" (Interview 13). Seven participants had problems understanding the changes in the weekly goals after completing an assessment element of the learning path personalization system: "Now, I have 3 out of 50 min. Previously, I had 3 out of 55 min. I'm surprised because I have not completed more minutes, but the minutes decreased" (Interview 7).

Design. Eight participants praised the clear layout of the TEPSI. However, some participants had difficulty identifying the most important information on the dashboard at first glance. For example, when presented with the screenshot "Overdue" (see Fig. 6), two participants thought that they still had three days until the deadline (instead of being three days late). Seven participants praised the colors of the dashboard: "I like the colors. Blue in the beginning, green in the end, yellow if your goal is at risk, and red if you have failed" (Interview 1). However, six participants would prefer a more eye-catching color scheme (e.g., green instead of blue to indicate progress). Four participants each praised the emojis and the text-based motivational messages. However, four participants thought that the emojis for the screenshots "First week", "On track, last weekly goal achieved", and "At risk, last weekly goal achieved" (see Fig. 6) did not match the text-based motivational messages or were not meaningful. Moreover, nine participants mentioned that some terms in the dashboard (e.g., atoms, at risk) were not appropriate for the context of learning: "At risk, I have a different association with that term [...] If I stand under a floating load of a crane, this is a risk, but on a learning platform, there is no risk" (Interview 14).

7.2.2. Research question 4: perceived usefulness

Goal Setting and Planning. Twelve participants reported that the indication of the average weekly learning time when setting an overall learning goal could help them get a realistic estimation of the time and effort needed to complete the learning path. Moreover, 12 participants reported that the TEPSI could support them in organizing their learning process by creating a learning plan. However, two participants mentioned that they would need specific recommendations to set realistic goals and perceived the average weekly learning time displayed when selecting a date as insufficient for specifying a realistic deadline: "Maybe in the beginning, the system could supply a recommendation for an ideal average weekly learning time [...] Otherwise, you might be too ambitious with your deadline" (Interview 15). Moreover, seven participants would prefer a greater degree of autonomy in organizing their weekly goals (e.g., the option to pause the system if they are on vacation

Table 9
Summary of the Findings of Study 2.

Main category	Positive aspects	Negative aspects
Research Question 3: Perceived ease of use		
Salience	• Intervention on the starting page • Setting an overall learning goal	• Intervention in the learning path overview • Accessing the dashboard and updating the deadline
Understandability	• Overall learning goal • General principles of the dashboard visualizations	• Confusion about different weekly goals • Timely progress in the dashboard does not represent actual learning time • Confusion about changes in weekly goals after completing an assessment element of the learning path personalization system
Design	• Clear layout • Colors based on progress • Emojis • Test-based motivational messages	• Problems in spotting the most important information at first glance • Colors are not eye-catching • Emojis do not match the text or are not meaningful • Some terms (e.g., atoms, at risk) are not appropriate for learning
Research Question 4: Perceived usefulness		
Goal setting and planning	• Realistic time and effort estimation • Learning plan	• Specific recommendations to set realistic goals are needed • Missing planning autonomy • No planning of learning content • Learning goals should be based on learning tasks and content
Self-monitoring	• Monitoring of learning progress	• No monitoring of learning content • Motivation to surface learning
Self-evaluation and reaction	• Developing an idea about one's weekly time resources • Possibility to change the deadline	• Missing recommendations for adapting the deadline • Missing summary on weekly goals • No reflection on learning content
Time and study environment	• Scheduling learning time • Monitoring learning time	• Missing calendar integration • Missing reminder • Weekly feedback is too unspecific • Missing specific support if weekly goals are not achieved
Effort regulation	• Commitment • Small steps • Seeing progress • Motivation for further learning paths	• Demotivating if the overall learning goal is at risk • Missing motivation through learning content • More gamification needed

or enhance the weekly goal for a specific week). Three participants criticized that the TEPSI did not help plan learning content, and two participants mentioned that meaningful learning goals should be based on learning tasks and content rather than time: “What are my personal goals? What do I want to achieve with this course? What do I want to achieve this week? The intervention does not help me analyze these questions” (Interview 7).

Self-Monitoring. Fifteen participants perceived the TEPSI as useful for monitoring their learning progress: “It helps me acquire an overview of my current status” (Interview 1). However, four participants criticized that the TEPSI did not help monitor their understanding of the learning content: “I cannot monitor how much I know already” (Interview 7). Moreover, one participant mentioned that the TEPSI might motivate surface learning, that is, to quickly click through the learning materials to see the progress in the dashboard rather than engaging deeply with the learning materials.

Self-Evaluation and Reaction. Thirteen participants reported that in the long term, the TEPSI could help them gain a realistic idea about their weekly time resources. Moreover, seven participants appreciated that the TEPSI allowed them to change the deadline: “I like it that you can change your goals if you realize that you need more time or that you are faster than expected” (Interview 4). However, four participants would prefer more specific recommendations for adapting their deadline: “Maybe some hints or a mouseover effect that shows what would change if you selected another deadline” (Interview 6). Moreover, seven participants missed a summary of their performance in the past weeks: “I would like to have a complete overview of my past progress […] I can review my last week, but […] I cannot reflect on what happened before” (Interview 14). Five participants also criticized that the TEPSI only helped reflect on time issues, but not on the learning content.

Time and Study Environment. Several participants perceived the TEPSI as useful for scheduling ($n = 6$) and monitoring ($n = 12$) their learning time: “The remaining time helps me get a feeling about how much I still need to do” (Interview 1). However, some participants expressed that they missed a direct connection to a calendar ($n = 3$) and reminders ($n = 2$): “That you get a reminder if you have not finished your workload by the end of the week” (Interview 12). Moreover, two participants would prefer more specific feedback on their weekly goals, such as a precise indication of how many minutes they need to catch up if they fall behind on their learning plan. Further, two participants would prefer more detailed support to enhance self-regulation when failing a weekly goal: “Maybe some recommendations for common problems or reasons for not achieving your goal” (Interview 6).

Effort Regulation. Seven participants reported that the TEPSI could create commitment toward the learning path. Participants also mentioned that the TEPSI enhanced their motivation by breaking the learning path into small steps ($n = 5$) and by visualizing their progress ($n = 18$): “It enhances my motivation because it says that I have made great progress” (Interview 2). Four participants mentioned that the TEPSI might motivate them to complete further learning paths after achieving the overall learning goal. However, twelve participants mentioned that the TEPSI only enhanced motivation as long as they were on track. If the overall learning goal is at risk, the TEPSI may create stress and cause dropout: “If you are not on track and the weekly goals increase continuously, the intervention creates a negative feeling […] The workload might become too heavy, and you might stop” (Interview 15). Moreover, four participants would prefer being motivated through learning content rather than time, and five participants would appreciate more gamification elements, such as badges for achieving weekly goals.

8. General discussion

SRL strategies have been considered essential for learning success in CE [6,7]. We evaluated the TEPSI of the edyoucated-platform, which aims to support metacognitive and resource management strategies in CE. While our experimental study (Study 1) showed limited effectiveness of the TEPSI in supporting learning processes, our qualitative interview study (Study 2) provided insights into its benefits (e.g., realistic time and effort estimation) and weaknesses (e.g., no planning of learning content).

8.1. Interpretation of results and theoretical implications

8.1.1. Context-dependent effects on self-reported time and study environment

Study 1 revealed a positive effect of the availability of the TEPSI on self-reported time and study environment, but only for the Data Reporting learning path. These findings are consistent with Xu et al.’s [91] meta-analysis showing that the effectiveness of SRL interventions in K-12 and higher education depend on the subject types, with greater effects observed for STEM than for non-STEM subjects. The findings highlight that TEPSIs are context-dependent and should be adaptive to not only learner characteristics and behavior but also to the respective learning content [66]. Previous research has highlighted that the learning content can shape SRL and online learning behaviors. For example, learners’ use of SRL strategies [66,92] and interaction patterns within online learning environments [93,94] vary across learning topics and disciplines. Moreover, characteristics of learning activities (e.g., duration, instructional strategies) can influence individual learning processes, such as SRL strategies [6] and learning engagement [95,96].

Although our studies cannot explain the reasons for the context-dependent effect of the TEPSI of the edyoucated-platform, we can make some assumptions. The Data Reporting learning path had a slightly longer total learning duration (approximately 6.5 h) than Agile Management (approximately 5.5 h) but was shorter than the Leadership in Practice (approximately 10 h) learning path. Possibly, the TEPSI’s weekly learning time recommendations are inappropriate for very short learning paths, such as Agile Management, which can be completed in just a few learning sessions and do not require resources to be regulated over several weeks. Further, a stronger focus on regulating motivational resources and sustaining interest might be needed to effectively support SRL and learning persistence in long learning paths [97], such as Leadership in Practice, where the dropout rate was significantly higher than in the other two learning paths. Moreover, the average learning duration per skill atom tended to be shorter in the Data Reporting learning path than in the other two learning paths (see Supplementary Material S1). Therefore, the Data Reporting learning path might have been more suitable and flexible for dividing the learning materials into meaningful weekly goals and adapting to individual learning behavior.

Furthermore, since participants in Study 1 were randomly assigned to conditions but not to the learning paths, self-selection bias [98] might have occurred. Thus, differences in learners’ dispositions may be another reason for the context-dependent effect of the TEPSI. For example, learners in the Data Reporting learning path might have exhibited enhanced data literacy, which might have helped them effectively use the TEPSI to support their learning processes [99–101]. Further, learners’ motivational dispositions, such as goal orientations and task value, might have differed between the learning paths and influenced the extent to which learners benefited from the TEPSI [102–104].

8.1.2. Drawbacks in supporting learning processes

The availability of the TEPSI did not show any significant effects on learning path completion and self-reported metacognitive self-regulation. Self-reported metacognitive self-regulation even decreased in both conditions over time. This decrease might be attributed to learners developing a more sophisticated and critical understanding of their metacognitive strategies during the learning period [21]. Given the lack of significant differences between the two conditions in terms of learning path completion and self-reported metacognitive self-regulation, we suggest that other factors (e.g., lack of time, unfulfilled expectations; [13,52]) might have played a more central role in participants' learning processes than the availability of the TEPSI. For instance, metacognitive strategies and the completion of learning materials require time and effort [33,105]. Even though the TEPSI of the edyoucated-platform aims to help learners regulate their time and effort resources, to a certain extent, sufficient resources need to be present as a precondition. For example, if learners do not have enough time available for learning, interventions that help them monitor and manage their insufficient time resources may not be beneficial [13,19]. Moreover, the findings of Study 1 revealed that interacting with the TEPSI of the edyoucated-platform might even negatively affect learning processes. While the percentage of achieved weekly goals was positively related to learning path completion and self-reported time and study environment, setting an overall learning goal had negative effects. These findings suggest that the TEPSI is only helpful as long as learners can stick to the weekly goals. Nevertheless, the findings of Study 1 alone cannot sufficiently explain the limited effectiveness of the TEPSI in supporting learning processes in CE, as the self-report questionnaire used to measure SRL strategies [31,32] might not have captured specific task-related and platform-specific SRL processes [106,107]. Therefore, Study 2 used the think-aloud method to gain more specific insights into SRL processes during interaction with the TEPSI.

Accordingly, Study 2 revealed further explanations for the TEPSI's limited effectiveness in supporting learning processes. For example, participants criticized its missing connection to the learning path's content. SRL involves planning, monitoring, and reflection behaviors that should consider both time and content aspects [31,32,36]. Moreover, participants in Study 2 wished for more support concerning specific features of the intervention, such as recommendations to set realistic goals or recommendations for adapting deadlines. These findings are consistent with previous research showing that learners might need specific instructions on how to make sense of dashboard visualizations [21]. Especially learners with limited SRL skills and feedback literacy might need more support to adequately use the information presented by the TEPSI [108,109]. Further, the TEPSI might not provide the necessary support to set high-quality goals, and the overall learning goals set by learners might lack feasibility, specificity, or personal relevance to effectively support learning processes [110,111].

Moreover, participants in Study 2 perceived the negative feedback provided by the TEPSI when they were not on track as demotivating. Continuous negative feedback may cause psychological reactance and, consequently, dropout [81]. Moreover, participants in Study 2 criticized the TEPSI for being too prescriptive in terms of time allocation and for not considering planned appointments (e.g., vacation), thereby limiting learner autonomy. Autonomy has been considered a key driver of intrinsic motivation [112,113]. Thus, if learners cannot achieve weekly goals due to planned appointments, the negative feedback provided by the TEPSI may be particularly demotivating. Even though the TEPSI aimed to promote learner control and autonomy by continuously adapting to individual learning behavior and by letting learners adjust their learning plan at any time, this was not sufficient to satisfy learners' need for autonomy.

Overall, participants in Study 2 perceived the TEPSI as intuitive and usable. Nevertheless, some issues with the ease of use were identified, especially regarding accessing the dashboard in the learning path overview and the calculation of the weekly goals. For example, some participants were confused because the weekly goals were not identical for all weeks. Further, several participants did not understand how the learning path personalization based on prior knowledge affected the weekly goals. These findings raise the question of whether learning systems can be too adaptive, as continuous adaptation and personalization may create complexity and confuse rather than help learners [77,78].

Altogether, our findings are consistent with findings from previous studies showing limited effectiveness of TEPSIs in supporting learning processes in CE (e.g., [19,21]). Despite the potential of TEPSIs discussed in previous literature [46,64], our findings show that personalization is no miracle cure and that the effectiveness of TEPSIs in supporting learning processes in CE may depend on the learning content. Further, our findings show that TEPSIs may even negatively affect learning processes by providing negative feedback, reducing learner autonomy, and creating complexity. Moreover, continuous support from TEPSIs might hinder SRL by making learners dependent rather than encouraging self-regulation [114,115]. Therefore, to design effective TEPSIs, it is crucial to consider learners' experiences and perceptions of such interventions. By understanding how learners interact with and what they think of specific features of TEPSIs, adverse side effects may be prevented [24,77]. Although previous studies have reported non-significant effects of TEPSIs on SRL and learning outcomes (e.g., [19,21]), previous research has mainly focused on the potential of TEPSIs rather than their negative side effects [46,91]. Whereas the general tendency in research to publish primarily successful interventions may lead to an overestimation of the potential of TEPSIs [116], our findings critically challenge this potential and shed light on the unexpected negative side effects of TEPSIs.

8.2. Practical implications

Our studies have several implications for the design of TEPSIs for CE. First, our findings highlight the context-dependency of TEPSIs and show that a TEPSI that is beneficial for one learning path may be useless for another. Therefore, before implementing TEPSIs for CE, their suitability for the intended context of use should be thoroughly examined. In this regard, learning systems could analyze data from previous learners who have completed a specific learning path to identify the most effective SRL strategies for the given learning content or to create an ideal learning plan based on the behaviors of the most successful learners. As such, more tailored TEPSIs can be created that consider not only learner characteristics and behaviors but also the specific learning content with which they engage [66].

Second, since TEPSIs that help learners regulate time and effort resources may not be beneficial if learners lack sufficient time for a specific CE activity [13,52], TEPSIs should help learners select an appropriate CE activity at the beginning of their learning process. For example, TEPSIs may include recommender systems in which learners can indicate their available learning time and are then recommended an appropriate learning path based on their individual time resources [58].

Third, TEPSIs for CE should provide holistic support for SRL, considering aspects related to both time and learning content [36,91,117]. For example, dashboards should visualize learning progress based on learning content rather than only time-related aspects [24]. Further, TEPSIs could provide personalized scaffolds that help learners apply appropriate strategies to engage with the learning materials [118].

Fourth, since learners in CE may have difficulties setting realistic learning goals [46] and making sense of dashboard visualizations [21], learners need specific instructions on how to use TEPSIs. For example, TEPSIs could provide personalized recommendations of realistic average weekly learning times based on the individual learner's previous learning behavior (e.g., average weekly time the learner has spent on the platform in the past weeks). Moreover, learners could be explicitly instructed to adapt their overall learning goal if it becomes unreachable. Otherwise, learners may be demotivated by continuous negative feedback [81].

Fifth, since learners in CE are distinguished by a strong need for self-direction [42,43], TEPSIs for CE should not be overly prescriptive and give learners autonomy in planning and organizing their learning processes [19]. For example, learners should not be prescribed weekly learning times, but should be allowed to decide for themselves how to allocate their learning time over the weeks. Such autonomy in planning and organizing learning processes may enhance self-regulation and prevent learners from becoming dependent on SRL support [114,115].

Sixth, continuous adaptation and personalization of learning activities can create complexity and reduce learners' perceived ease of use

[77,78]. Therefore, TEPSIs should provide specific explanations regarding the SRL support [119,120]. For example, mouseover effects could clarify dashboard visualizations [121].

8.3. Limitations and future research

Our studies have some limitations that provide implications for future research. First, although Study 1 suggests that the TEPSI of the edyoucated-platform is more effective for the Data Reporting learning path than for the other two learning paths, the concrete reasons for this context-dependent effect were not examined. Future research should investigate what characteristics of CE activities (e.g., duration) moderate the effects of TEPSIs on learning outcomes and SRL in CE. Moreover, future research should investigate whether learner characteristics (e.g., digital literacy, motivational dispositions) affect the effectiveness of TEPSIs in supporting learning processes in CE.

Second, it was challenging to recruit participants for Study 1 who were willing to invest several hours in a voluntary CE activity. Consequently, many participants dropped out between the pre- and the post-questionnaire, and the sample size was rather small, particularly when considering the three learning paths separately. Moreover, the selection of and the subgroup analyses for the three learning paths were exploratory. Future research should manipulate specific characteristics of learning paths based on theory-driven criteria and examine TEPSIs for CE using a larger samples to enable more meaningful analyses of differences between learning paths. In this regard, project collaborations with business organizations may be useful to attract a large pool of potential participants.

Third, the measures of the dependent variables employed in Study 1 may be subject to some biases. For example, since the study was conducted entirely online, we had no control over how deeply participants engaged with the learning materials. Thus, the measurement of learning path completion might be biased. While the ecological validity ensured by the authentic CE setting is a clear strength of Study 1, future research should evaluate TEPSIs for CE in more controlled settings to enhance internal validity and to employ a more profound measurement of learning path completion [122]. Moreover, the self-reported SRL strategies might be subject to subjective biases, such as social desirability [123,124] or individual response styles [125]. Further, the effort regulation subscale was subject to unsatisfactory reliability scores. Therefore, future research should employ behavioral measures of SRL strategies [126] to investigate the effectiveness of TEPSIs.

Fourth, Study 2 only captured participants' first impressions of the TEPSI, as participants did not use the intervention while completing a learning path on the edyoucated-platform. Therefore, participants' perceptions of the TEPSI might be biased. For practical reasons and to gain insights into participants' cognitive processes during interaction with the TEPSI, we opted for the think-aloud method instead of conducting retrospective interviews with participants from Study 1. However, the different application scenarios of the two studies (12-week learning period vs. think-aloud interviews to capture first impressions) may limit the validity of Study 2 in explaining the findings of Study 1. Therefore, future research should qualitatively investigate learners' perceptions of TEPSIs after using such interventions during their learning process.

Fifth, although the practical implications discussed in Section 8.2 may inform the design of TEPSIs in CE, the generalizability of our findings is limited because the TEPSI examined is specifically tailored to the design and structure of the edyoucated-platform. Therefore, future research should build on our findings and design and evaluate TEPSIs for a wider variety of CE activities and learning environments.

8.4. Conclusion

CE has been considered important for keeping knowledge, skills, and competences up-to-date [1,2] and requires learners to engage in SRL [7,8]. Researchers have emphasized the potential of educational technologies to provide personalized support for SRL [46,64]. However, robust empirical evidence for designing effective TEPSIs for CE remains scarce. Therefore, this paper introduced a TEPSI to address common SRL challenges in CE, evaluated the effectiveness of this TEPSI in supporting learning processes in CE, and investigated learners' perceptions of the TEPSI. The findings revealed ambivalent and context-dependent effects of the TEPSI on learning path completion and self-reported SRL strategies. Moreover, several issues regarding learners' perceived ease of use and usefulness of the TEPSI were identified, which may prevent learners from engaging actively and effectively with the TEPSI. Overall, our studies show that personalization is no miracle cure and that improper implementation of TEPSIs can negatively impact learning processes. Our findings highlight the importance of studying learners' experiences and perceptions of TEPSIs and provide implications for reducing the negative side effects of such interventions.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used DeepL, QuillBot Grammar Checker, and Grammarly to check for linguistic errors and improve the manuscript's readability. After using these tools/services, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Research data

An anonymized version of the datasets can be provided upon reasonable request.

CRediT authorship contribution statement

Yvonne M. Fromm: Writing – original draft, Visualization, Software, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Dirk Ifenthaler:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Julian Rasch:** Writing – review & editing, Visualization, Validation, Resources, Project administration, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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