Adaptive Learning Environments and Self-Regulated Learning in Continuing Education:

A Multi-Method Approach Toward Robust Empirical Evidence

Inaugural Dissertation
to Obtain the Academic Degree of a Doctor in Business Administration at the University of Mannheim

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Mannheim, 2025

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Day of oral examination: March 9, 2026

Abstract

Due to rapid technological, social, and economic developments, continuing education (CE) is becoming increasingly important for individuals to adapt to ever-changing (work) requirements, tasks, and practices. Learners may enter a CE activity with different prerequisites and expectations, such as varying levels of prior knowledge, different learning goals, and diverse interests. Therefore, a major challenge in designing effective CE activities is creating learning activities that cater to a heterogeneous group of learners. Moreover, many learners in CE struggle to engage successfully in self-regulated learning (SRL), which includes the regulation of cognitive, affective, behavioral, and contextual resources during learning and has been considered essential for learning success in CE. In this regard, researchers have recognized the potential of adaptive learning environments (ALEs) to provide personalized learning experiences and support SRL through dashboards, real-time feedback, and learning recommendations. However, there is a lack of robust empirical evidence and frameworks for designing ALEs and supporting SRL in CE. Therefore, this thesis aims to promote user-centered design approaches by providing empirical insights into ALEs and SRL in CE.

The thesis consists of four independent research papers that employ qualitative and quantitative research methods. In Paper 1, interviews, focus groups, and an online survey were conducted to investigate different stakeholders' (learners', CE specialists', and educational technology specialists') perspectives on ALEs for CE. Several indicators (i.e., variables that reveal useful information about learners and their contexts) and interventions (i.e., measures for personalizing and supporting learning processes) relevant to CE were identified and organized into a design framework for ALEs. Based on this framework, Paper 2 employs an experimental study to evaluate an ALE that tailors learning activities to individual learners' prior knowledge. The findings of Paper 2 demonstrate that the effects of ALEs on learning outcomes in CE depend on learners' motivational dispositions. Paper 3 comprises a systematic review and meta-analysis to explore the nature of SRL in CE and highlights learning process-related, learner-related, CE-related, and work-related factors that may support or hinder SRL in CE. In Paper 4, an intervention to support SRL in CE was evaluated using an experimental and an interview study. The findings show that the effectiveness of ALEs in supporting SRL varies across different learning content. Moreover, the findings highlight that personalization may have negative side effects on SRL, for example, by impairing motivation through constant negative feedback or reducing the ease of use through complex adaptation.

Overall, this thesis provides guidance on designing and implementing ALEs for CE. Through empirically investigating the perspectives of different stakeholders and the effectiveness of ALEs in CE, this thesis highlights the benefits and weaknesses of ALEs for CE and encourages the development of user-centered and evidence-based ALEs. However, additional research is needed to shed further light on the context-dependent effects of ALEs on (self-regulated) learning processes in CE, as well as to explore the role of human instructors and ethical guidelines for implementing ALEs in CE.

Zusammenfassung

Aufgrund rasanter technologischer, sozialer und wirtschaftlicher Entwicklungen wird Weiterbildung immer wichtiger, um sich an ständig ändernde (berufliche) Anforderungen, Aufgaben und Praktiken anzupassen. Lernende können mit unterschiedlichen Voraussetzungen und Erwartungen, wie beispielsweise unterschiedlichem Vorwissen, unterschiedlichen Lernzielen und unterschiedlichen Interessen, an einer Weiterbildung teilnehmen. Eine Herausforderung bei der Gestaltung effektiver Weiterbildungsmaßnahmen besteht daher darin, Lernaktivitäten zu entwickeln, die auf eine heterogene Gruppe an Lernenden zugeschnitten sind. Ferner haben Lernende in der Weiterbildung häufig Schwierigkeiten, sich erfolgreich auf selbstreguliertes Lernen einzulassen. Selbstreguliertes Lernen bezeichnet die Regulierung von kognitiven, affektiven, verhaltensbezogenen und kontextuellen Ressourcen während des Lernens und wird als wesentlich für Lernerfolg in der Weiterbildung angesehen. In diesem Zusammenhang haben Forschende das Potenzial von adaptiven Lernumgebungen erkannt, um Lernprozesse in der Weiterbildung zu personalisieren und selbstreguliertes Lernen durch Dashboards, Echtzeit-Feedback und Lernempfehlungen zu unterstützen. Es fehlen jedoch robuste empirische Befunde und Designkonzepte für die Gestaltung von adaptiven Lernumgebungen und die Unterstützung von selbstreguliertem Lernen in der Weiterbildung. Ziel der vorliegenden Arbeit ist es daher, nutzerzentrierte Designkonzepte zu fördern, indem sie empirische Einblicke in adaptive Lernumgebungen und selbstreguliertes Lernen in der Weiterbildung liefert.

Die vorliegende Arbeit besteht aus vier unabhängigen Artikeln mit sowohl qualitativen als auch quantitativen Forschungsmethoden. In Artikel 1 wurden Interviews, Fokusgruppen und eine Online-Umfrage durchgeführt, um die Perspektiven von unterschiedlichen Stakeholdern (Lernende sowie Experten/-innen aus den Bereichen Weiterbildung und Bildungstechnologien) zu untersuchen. Dabei wurden mehrere Indikatoren (d. h. Variablen, die nützliche Informationen über Lernende und deren Kontext liefern) und Interventionen (d. h. Maßnahmen zur Personalisierung und Unterstützung von Lernprozessen) für den Kontext der Weiterbildung identifiziert und in einem Design-Framework für adaptive Lernumgebungen zusammengefasst. Basierend auf diesem Design-Framework wurde in Artikel 2 eine experimentelle Studie durchgeführt, um eine adaptive Lernumgebung zu evaluieren, die Lernaktivitäten an das Vorwissen der einzelnen Lernenden anpasst. Die Ergebnisse von Artikel 2 zeigen, dass die Effekte von adaptiven Lernumgebungen auf Lernergebnisse in der Weiterbildung von der Motivation der Lernenden abhängen. Artikel 3 umfasst eine

systematische Literaturübersicht und eine Meta-Analyse, um empirische Einblicke in selbstregulierte Lernprozesse in der Weiterbildung zu gewinnen. Die Ergebnisse geben Einblicke in verschiedene Faktoren des Lernprozesses, der Lernenden, der Weiterbildung und des Arbeitsplatzes, die selbstreguliertes Lernen in der Weiterbildung fördern oder hemmen können. In Artikel 4 wurde eine Intervention zur Unterstützung von selbstreguliertem Lernen in der Weiterbildung entwickelt und anhand einer experimentellen Studie und einer Interviewstudie evaluiert. Die Ergebnisse zeigen, dass die Wirksamkeit von adaptiven Lernumgebungen zur Unterstützung von selbstreguliertem Lernen in der Weiterbildung je nach Lerninhalt variiert. Darüber hinaus heben die Ergebnisse hervor, dass Personalisierung negative Nebeneffekte auf selbstreguliertes Lernen haben kann, beispielsweise indem sie die Motivation der Lernenden durch ständiges negatives Feedback beeinträchtigt oder die Benutzerfreundlichkeit durch kontinuierliche Anpassungen reduziert.

Die vorliegende Arbeit bildet eine Grundlage für die Entwicklung und Implementierung von adaptiven Lernumgebungen für die Weiterbildung. Durch empirische Einblicke in die Perspektiven verschiedener Stakeholder sowie in die Wirksamkeit von adaptiven Lernumgebungen für die Weiterbildung hebt die Arbeit die Stärken und Schwächen von adaptiven Lernumgebungen hervor und regt zur Entwicklung von nutzerzentrierten und evidenzbasierten adaptiven Lernumgebungen für die Weiterbildung an. Weitere Forschung ist erforderlich, um die kontextabhängigen Effekte von adaptiven Lernumgebungen in der Weiterbildung besser zu verstehen und die Rollen menschlicher Lehrkräfte sowie ethische Richtlinien für die Implementierung von adaptiven Lernumgebungen in der Weiterbildung zu untersuchen.

Acknowledgements

Preparing this thesis and conducting the research it contains has been a very enriching experience for me, both professionally and personally. I would like to thank everyone who has supported and accompanied me throughout the journey of this dissertation project.

First and foremost, I would like to express my deepest gratitude to my supervisor Professor Dr. Dr. h.c. Dirk Ifenthaler for giving me the opportunity to do this thesis within his wonderful research group. I am deeply grateful for his trust, the freedom he has given me in my research, and his unwavering and always helpful support. His enthusiasm for research, his valuable feedback, and his thoughtful guidance have continuously encouraged and inspired me in my work. I could not have wished for a better supervisor.

Moreover, I would like to express my gratitude to Professor Dr. Jürgen Seifried and Dr. Yi-Shan Tsai for agreeing to serve as additional reviewers of this thesis. I am very grateful for their time and effort.

In addition, I would like to thank the team from edyoucated for the continuous exchange and the fruitful research collaboration, without which several of the studies included in this thesis would not have been possible. Special thanks go to Dr. Julian Rasch, who has always been supportive and with whom I have had many insightful discussions that have inspired me in my work. Moreover, I would like to thank the German Federal Ministry of Education and Research as well as the German Federal Institute for Vocational Education and Training for the provided project funding (funding reference 21INVI01).

I am also thankful for all my supportive colleagues at the Area of Economic and Business Education. In particular, I would like to thank Floris Scherb for his helpful comments and the fruitful exchange. Special thanks also go to Dr. Jan Delcker, who gave me a warm welcome in Mannheim and helped me a lot in the beginning, and to Joana Heil, who suffered with me during the last steps of this journey and with whom I spent many inspiring and fun office days and lunch breaks. I would also like to thank my other current and former colleagues at the Chair of Learning, Design and Technology for the wonderful time we had (and still have) together: Jasmin Banjac, Dr. Li Chen, Dr. Marc Egloffstein, Xueqing Han, Nicolai Plintz, Ivan Polivanov, Xinjie Xing, and Julia Zinsmeister. I would also like to take this opportunity to thank all our (former) student assistants, especially Julia Spuck, for their support.

Finally, I would like to thank my family and friends for their support and encouragement. I am especially grateful to my parents, who have always supported me and believed in me, regardless of which path I chose to take. My greatest thanks go to my husband

Tobias, who has been my rock during this journey. Thank you for standing by my side, putting up with my bad moods during difficult times, and boosting my self-confidence when needed. Your emotional support has contributed significantly to the success of this thesis!

For Tobias

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List of Abbreviations

The following abbreviations are used in the running text of this thesis. Abbreviations only used in tables and figures are explained in the corresponding table and figure captions.

AI	artificial intelligence
ALE	adaptive learning environment
BMBF	Bundesministerium für Bildung und Forschung (Federal Ministry of Education and Research)
CE	continuing education
GDPR	General Data Protection Regulation
LLM	large language model
MOOC	Massive Open Online Course
MSLQ	Motivated Strategies for Learning Questionnaire
PKQ	personalization based on knowledge questions
PSRQ	personalization based on self-report questions
SRL	self-regulated learning
TEPLE-PK	technology-enhanced personalized learning environment based on prior knowledge
TEPSI	technology-enhanced personalized self-regulated learning intervention

1. Introduction

1.1 The Relevance of Adaptive Learning Environments and Self-Regulated Learning in Continuing Education

1.1.1 The Need for Adaptive Learning Environments in a Rapidly Changing (Working) World

Technological, social, and economic developments are constantly and rapidly changing today's society, work tasks, and work practices (Littlejohn & Pammer-Schindler, 2022; World Economic Forum, 2025). For example, the expansion of digital access and the rise of artificial intelligence (AI) and automation technologies are transforming workplaces, leading to increased job complexity (L. Li, 2024; World Economic Forum, 2025). Due to the high speed of these developments and changes, individuals are required to acquire new knowledge, skills, and competences on an ongoing basis (Littlejohn & Pammer-Schindler, 2022; Omar et al., 2024). Formal qualifications gained from K-12 education, professional apprenticeships, or higher education are no longer sufficient to master the demands of everyday life and a lifelong professional career (Bayly-Castaneda et al., 2024; Littlejohn & Pammer-Schindler, 2022). Hence, the idea that learning is a lifelong process has become prominent and has led to a growing demand for continuing education (CE) opportunities that support individuals to keep their knowledge, skills, and competences up-to-date (Bayly-Castaneda et al., 2024; Mlambo et al., 2021).

In this regard, traditional classroom-based CE activities teaching standard curricula are not flexible enough to meet the strong demand for learning opportunities and rapidly changing requirements of today's (working) world. Researchers have called for shorter and more focused CE activities that are readily accessible and assist learners in solving immediate problems in everyday (work) life (Fidalgo & Thormann, 2024; Littlejohn & Pammer-Schindler, 2022). Consequently, technological advances have been considered a catalyst for reshaping CE practices and have led to a significant increase in CE activities offered online (Bundesministerium für Bildung und Forschung [BMBF], 2024; Littlejohn & Pammer-Schindler, 2022; Omar et al., 2024). For example, online learning platforms offering Massive Open Online Courses (MOOCs) or other synchronous and asynchronous online courses have become popular as a means of providing learning opportunities to a large number of learners and enabling individuals to gain small-scale qualifications, which can be completed within a few days or weeks (Littlejohn & Hood, 2018; Littlejohn & Pammer-Schindler, 2022).

However, one major challenge in designing effective CE activities remains the conception of learning activities that cater to an increasingly heterogeneous group of learners (Fake & Dabbagh, 2020; Omar et al., 2024; Rasch & Middelbeck, 2022). Learners in CE usually differ in their (professional) backgrounds and prior experiences and may enter a CE activity with different prerequisites and expectations, such as varying levels of prior knowledge, different learning goals, and diverse interests, that may impact individual learning processes (Knowles et al., 2012; Meister & Willyerd, 2021; Plass & Pawar, 2020b; Rasch & Middelbeck, 2022). The increase in CE activities offered online has reinforced this heterogeneity of the learner base, as online learning can provide access to learning opportunities for a large number of learners (Littlejohn & Pammer-Schindler, 2022; Raj & Renumol, 2024; Rasch & Middelbeck, 2022). Moreover, the vast amount of learning resources and CE activities available online may lead to information overload and challenge learners to find appropriate learning activities that align with their individual prerequisites and expectations (Eriksson et al., 2017; Raj & Renumol, 2018; Wu et al., 2020).

Hence, recent research on educational technologies has recognized the potential of adaptive learning environments (ALEs) for providing personalized learning experiences and supporting learning processes in CE (Bayly-Castaneda et al., 2024; Chaipidech et al., 2022; Gharahighehi et al., 2024a). ALEs are digital learning systems (e.g., learning platforms, learning apps) that analyze data about learners and their contexts to tailor learning activities to the individual learner and to support learning processes (Hemmler & Ifenthaler, 2022b; Plass & Pawar, 2020a; Xie et al., 2019). For example, ALEs may analyze learners' individual levels of prior knowledge to offer personalized learning paths (Rasch & Middelbeck, 2022), provide recommender systems that suggest learning resources based on individual learning goals (Hemmler et al., 2023), or adapt the difficulty level of learning materials based on individual learning performance (González-Castro et al., 2021). In this way, ALEs may improve the alignment between learners' individual needs and CE activities, helping learners achieve their personal learning goals by providing appropriate learning resources and preventing them from being over- or underchallenged (Omar et al., 2024; Plass & Pawar, 2020a; Rasch & Middelbeck, 2022). Moreover, in addition to providing opportunities for personalized learning, ALEs may support the optimization of instructional design and curricula by identifying and adapting to common learner challenges, such as common comprehension difficulties or errors in quiz questions (Aleven et al., 2017).

The increasing use of educational technologies for online learning, coupled with increased computing power, has fueled the development of ALEs by enabling the collection and analysis of large amounts of education-related data that may provide useful insights into individual learning processes (Gharahighehi et al., 2024b; Gligorea et al., 2023; K. C. Li & Wong, 2023). Moreover, advances in the field of AI have offered methods for analyzing large datasets and opportunities for automated personalized instruction (Ayeni et al., 2024; Hardaker & Glenn, 2025; Zawacki-Richter et al., 2019). For example, machine learning methods may be applied to predict learning performance and identify learners at risk of dropping out from a course, which may enable the provision of appropriate support tailored to learners' individual needs (Alonso et al., 2025; Zawacki-Richter et al., 2019). Further, chatbots based on large language models (LLMs) may serve as virtual tutors providing real-time feedback and personalized guidance (Ifelebuegu et al., 2023; Naznin et al., 2025).

1.1.2 The Role of Self-Regulated Learning

With learning environments becoming increasingly flexible, learners are required to take responsibility for their learning and self-regulate their learning processes (Min & Nasir, 2020; Teich et al., 2024). For example, to participate successfully in CE activities, learners need to define personal learning goals, manage their study time and motivational resources, apply appropriate learning strategies, and self-monitor their learning progress (Fontana et al., 2015; Min & Nasir, 2020; Prasse et al., 2024). While in traditional classroom-based CE activities, external regulation can be provided through fixed teaching times and locations, as well as supportive instructors, online CE activities are less externally regulated and demand stronger self-regulatory abilities (Broadbent & Poon, 2015; Guntur & Purnomo, 2024; Milligan & Littlejohn, 2016). Moreover, learners in CE usually have to balance learning with conflicting responsibilities, such as family and professional commitments, which may limit the time they have available for learning and cause distractions (Eriksson et al., 2017; Schröer et al., 2022; Teich et al., 2024). Therefore, efficient time management and effort regulation strategies are crucial for learning persistence in CE (Nawrot & Doucet, 2014; Teich et al., 2024). Hence, learners' abilities to engage in self-regulated learning (SRL), which includes the regulation of cognitive, affective, behavioral, and contextual resources during learning (Pintrich, 2000; Zimmerman & Schunk, 2011), have been considered a key competence for learning success in CE (Chaker & Impedovo, 2021; Lee et al., 2019; Teich et al., 2024).

However, learners in CE may struggle to engage successfully in SRL, which can result in dropouts and poor learning performance (Chen & Jang, 2019; Eriksson et al., 2017; Nawrot & Doucet, 2014). Therefore, researchers have recognized the need to foster SRL processes and have begun to use ALEs to support SRL in CE (Nguyen et al., 2024; Teich et al., 2024). For example, ALEs may provide personalized dashboards that visualize specific indicators of learning behavior to offer real-time feedback on SRL processes (D. Davis et al., 2016; Pérez-Álvarez et al., 2020). Further, ALEs may offer personalized prompts that facilitate appropriate learning strategies (Khiat, 2022; Schumacher & Ifenthaler, 2021) or personalized recommendations of learning content to help learners focus their attention and effort (Teich et al., 2024).

Thus, in summary, ALEs provide potential for offering flexible and personalized learning opportunities that satisfy the strong demand for CE in today's rapidly changing and constantly evolving (working) world (Omar et al., 2024). By enhancing the fit between learners and CE activities and by facilitating SRL processes, ALEs may contribute to the design of effective and efficient learning experiences, thereby promoting learning persistence (Khiat, 2022; Tzeng et al., 2024).

1.2 Research Gaps and Overarching Research Question of This Thesis

Despite the potential of ALEs for supporting learning processes in CE (Gharahighehi et al., 2024b; Nguyen et al., 2024), the implementation of ALEs in CE still faces significant challenges. For example, researchers have discussed conceptual challenges (e.g., lack of uniform terminology and definitions of the concepts related to ALEs), institutional challenges (e.g., resistance to change and lack of technological infrastructure to implement ALEs), technological challenges (e.g., algorithmic limitations and difficulties interpreting complex algorithms), ethical challenges (e.g., privacy concerns and potential misuse of sensitive data), psychological challenges (e.g., distrust and lack of learner engagement with ALEs), and pedagogical challenges (e.g., lack of pedagogical knowledge on how to adapt learning activities) associated with the development and implementation of ALEs (Barrera Castro et al., 2025; Strielkowski et al., 2025). Moreover, robust empirical evidence regarding the effectiveness of ALEs in supporting learning processes in CE and empirically-based frameworks for designing ALEs for CE are missing (Bernacki et al., 2021; Gharahighehi et al., 2024b; K. C. Li & Wong, 2023). For example, effective ALEs require reliable indicators and interventions. Indicators are specific variables that reveal useful information about learners and their contexts and that are collected and analyzed by ALEs. Interventions are measures for personalizing and supporting learning processes that are derived by ALEs on the basis of these indicators (Plass & Pawar, 2020b; Yau & Ifenthaler, 2020). Although the selection of reliable indicators and interventions has been considered central to the design of ALEs (Aleven et al., 2017; K. C. Li & Wong, 2023; Plass & Pawar, 2020b; Yau & Ifenthaler, 2020), empirical guidance for selecting indicators and interventions for ALEs for CE is still missing (Barrera Castro et al., 2025; Kaliisa et al., 2022; Plass & Pawar, 2020b).

To ensure that ALEs meet the needs and requirements of different stakeholders, such as learners, CE specialists, and educational technology specialists, researchers have emphasized the importance of user-centered design approaches that actively involve relevant stakeholders (Gharahighehi et al., 2024b; Gril et al., 2022; Schumacher & Ifenthaler, 2018a; Topali et al., 2025). A user-centered and empirically-based design framework may provide guidance for designing trustworthy ALEs that overcome implementation challenges in CE practice (Fake & Dabbagh, 2020; Klostermann & Kluy, 2025; Schumacher et al., 2019; Topali et al., 2025). However, many studies on ALEs for CE have focused on the technological aspects of ALEs without fully considering the perspectives of different stakeholders (Gharahighehi et al., 2024b; Tavakoli et al., 2022; Xue-jun et al., 2021).

Moreover, while recent meta-analyses have shown positive effects of ALEs on learning performance (Hooshyar et al., 2024; Hu, 2024; Lin et al., 2024; Tlili et al., 2024; Wang et al., 2024), learner satisfaction (Adam et al., 2024), and interest (Lin et al., 2024) in K-12 and higher education, experimental studies evaluating ALEs in the context of CE are scarce (Bernacki et al., 2021; K. C. Li & Wong, 2023; Viberg et al., 2020). Researchers have argued that learning in CE differs from K-12 and higher education (Knowles et al., 2012; Tynjälä, 2008; Wozniak, 2020). For example, according to adult learning theory, learners in CE are distinguished by their unique life experiences (Knowles, 1985; Knowles et al., 2012). Compared to K-12 and higher education students, learners in CE have accumulated more life experiences. Therefore, they tend to be more heterogeneous in terms of prior knowledge, learning goals, strategies, and interests (Knowles et al., 2012; Meister & Willyerd, 2021; Wozniak, 2020). In addition, learners in CE are characterized by a strong need for self-direction (Knowles, 1985; Knowles et al., 2012; Manning, 2007) and are usually given a higher degree of autonomy to decide when, how, and what they would like to learn than learners in K-12 and higher education (Sitzmann & Ely, 2011). Moreover, learners in CE typically have to balance learning with more concurrent commitments (e.g., work, family) than K-12 and full-time higher education students (Eriksson et al., 2017; Schröer et al., 2022). While learning is the main occupation of K-12 and full-time higher education students, CE usually takes place alongside the learners' main occupation (e.g., work; Eriksson et al., 2017; Schröer et al., 2022; Teich et al., 2024). Due to these differences, the relevance and effects of ALEs, as well as the need for effective SRL support, might differ between CE and K-12 and higher education. Hence, the findings of studies focusing on K-12 and higher education may not be completely reliable and valid when applied to CE, and more experimental studies for the context of CE are needed.

Moreover, considering the potential of ALEs for fostering SRL, most ALEs for supporting SRL in CE are based on SRL theories (e.g., Pintrich, 2000; Zimmerman, 2000) that were developed for K-12 and higher education (Cerón et al., 2020). Although researchers have emphasized the importance of SRL for CE (Min & Nasir, 2020; Teich et al., 2024), the nature of SRL in CE remains unclear, as comprehensive systematic reviews and meta-analyses investigating how SRL unfolds in CE are missing. Consequently, the effectiveness of ALEs in supporting SRL in CE still falls short of the expected potential (Prasse et al., 2024; Teich et al., 2024). For example, studies have shown that learners in CE rarely engage with ALEs to support their SRL (Cobos, 2023; Pérez-Álvarez et al., 2020; Teich et al., 2024). To investigate the reasons for these low engagement rates, it is necessary to gain a more profound understanding of how learners in CE perceive and evaluate ALEs. For example, insights into learners' perceived ease of use and usefulness of ALEs for supporting SRL may help identify barriers and enablers to learners' engagement with ALEs (F. D. Davis, 1986; Granić, 2022; Granić & Marangunić, 2019).

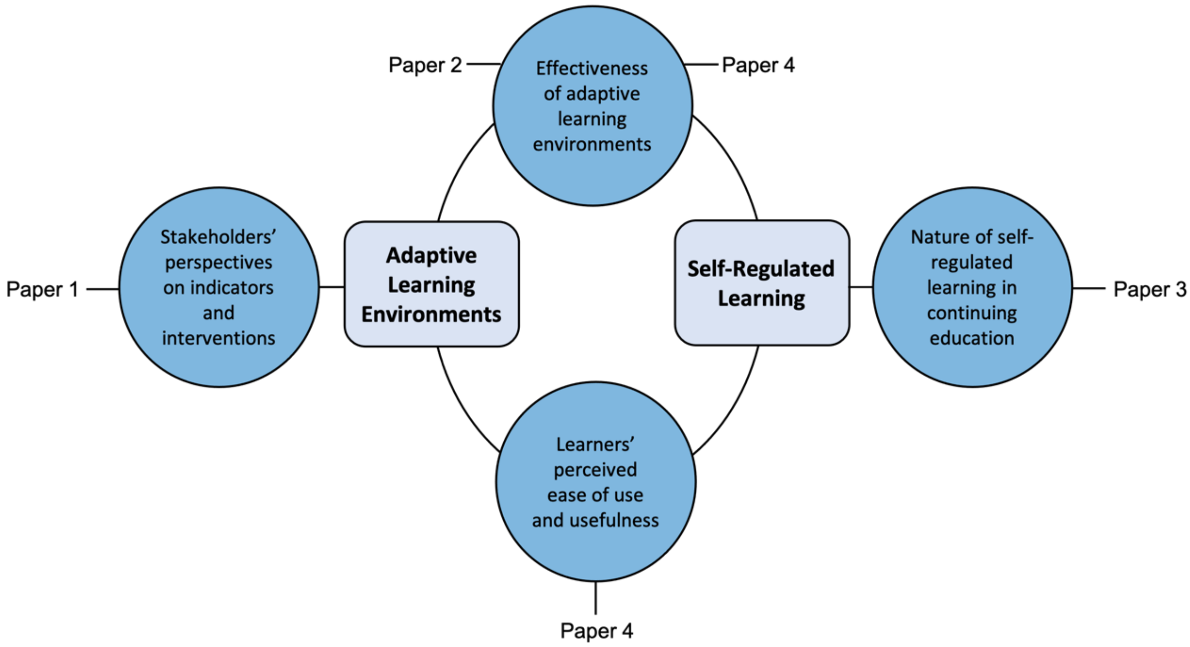
Hence, to address these research gaps, this thesis aims to fuel user-centered design approaches and empirical evidence on ALEs and SRL in CE by answering the following overarching research question: *How can the design of ALEs for CE be optimized to support SRL and positive learning outcomes?* As illustrated in Figure 1-1, the thesis comprises four independent research papers that address different foci of this overarching research question by

- exploring relevant stakeholders' perspectives on indicators and interventions for ALEs for CE (Paper 1).
- experimentally evaluating the effectiveness of ALEs in supporting learning processes in CE (Paper 2 and Paper 4).
- examining the nature of SRL in CE (Paper 3).
- investigating learners' perceived ease of use and usefulness of ALEs for supporting SRL in CE (Paper 4).

These insights may provide a useful basis for designing trustworthy and advantageous ALEs for CE and help develop a profound understanding of the benefits and weaknesses of ALEs in supporting learning processes in CE.

Figure 1-1

Overview of the Research Foci of This Thesis



1.3 Specific Research Questions of This Thesis

The four papers answer specific research questions that reflect the overarching research question of this thesis. Together, the papers adopt a multi-method approach, including interviews, focus groups, an online survey, experimental studies, as well as a systematic review and meta-analysis. Table 1-1 presents a detailed overview of the four papers, their methodological approaches, and their research objectives.

Table 1-1

Overview of the Papers Included in This Thesis

	Paper 1 (Chapter 3)	Paper 2 (Chapter 4)	Paper 3 (Chapter 5)	Paper 4 (Chapter 6)
Reference	Fromm, Y. M., & Ifenthaler, D. (2024). Designing adaptive learning environments for continuing education: Stakeholders' perspectives on indicators and interventions. *Computers in Human Behavior Reports*, *16*, Article e100525. https://doi.org/10.1016/j.chbr.2024.100525	Fromm, Y. M., Rasch, J., & Ifenthaler, D. (2025). Technology-enhanced personalized learning environments based on prior knowledge in continuing education: An experimental study. *Smart Learning Environments*, *12*, Article e54. https://doi.org/10.1186/s40561-025-00407-z	Hemmler, Y. M., & Ifenthaler, D. (2024). Self-regulated learning strategies in continuing education: A systematic review and meta-analysis. *Educational Research Review*, *45*, Article e100629. https://doi.org/10.1016/j.edurev.2024.100629	Fromm, Y. M., Ifenthaler, D., & Rasch, J. (under review). Personalization is no miracle cure: Evaluation of a technology-enhanced self-regulated learning intervention for continuing education. *Computers and Education Open*.
Journal impact factor [a]	5.8	12.1	10.6	5.7
Design	• Study 1: qualitative • Study 2: qualitative • Study 3: quantitative	Quantitative	Qualitative & quantitative	• Study 1: quantitative • Study 2: qualitative
Method	• Study 1: interviews • Study 2: focus groups • Study 3: online survey	Experimental study	Systematic review & meta-analysis	• Study 1: experimental study • Study 2: think-aloud interviews
Sample	• Study 1: $N = 37$ learners • Study 2: $N = 19$ learners ($n = 10$) and specialists in CE and educational technology ($n = 9$) • Study 3: $N = 72$ learners ($n = 54$) and specialists in CE and educational technology ($n = 18$)	$N = 194$ learners	$N = 58$ primary studies	• Study 1: $N = 146$ learners • Study 2: $N = 20$ learners
Objectives	• Identify indicators and interventions for ALEs for CE by investigating the perspectives of different stakeholders • Develop a user-centered and empirically-based framework for selecting indicators and interventions for ALEs for CE	• Evaluate the effects of personalization based on prior knowledge on knowledge increase, learning path completion, and learner satisfaction in CE • Investigate how learners' goal orientations and task value moderate these effects	• Identify factors associated with learners' use of SRL strategies in CE • Investigate the strength and potential moderators of the underlying relationships	• Evaluate the effects of an SRL intervention on learning path completion and perceived SRL in CE • Investigate learners' perceived ease of use and usefulness of the intervention

Note. ALEs = adaptive learning environments, CE = continuing education, SRL = self-regulated learning.
[a] Two-year impact factor of 2024 as indicated on the journal's website (Computers in Human Behavior Reports: https://www.sciencedirect.com/journal/computers-in-human-behavior-reports, Smart Learning Environments: https://slejournal.springeropen.com/, Educational Research Review: https://www.sciencedirect.com/journal/educational-research-review, Computers and Education Open: https://www.sciencedirect.com/journal/computers-and-education-open).

1.3.1 Paper 1: Designing Adaptive Learning Environments for Continuing Education: Stakeholders' Perspectives on Indicators and Interventions

Paper 1 aims to identify reliable indicators and interventions for ALEs for CE and to develop a user-centered and empirically-based framework to guide the design and implementation of ALEs for CE. Researchers have argued that the search for indicators and interventions requires theoretical and empirical answers and that ALEs should only consider indicators that are relevant to achieving desired learning processes and outcomes (Aleven et al., 2017; Plass & Pawar, 2020b). Previous research has shown that learners' internal conditions (e.g., prior knowledge), which encompass personal and subjectively perceived learning experiences, dispositions, and beliefs, as well as external conditions (e.g., time), which encompass objective and predefined characteristics of the learning context, can impact learning processes and outcomes (Greene & Azevedo, 2007; Hemmler & Ifenthaler, 2022a; Tynjälä, 2013; Winne, 2022; Winne & Hadwin, 1998). Therefore, ALEs should consider indicators related to relevant internal and external conditions to derive adequate interventions for personalizing and supporting learning processes (Gašević et al., 2015, 2016; Hemmler & Ifenthaler, 2022a). Hence, Paper 1 focuses on identifying indicators that describe internal and external conditions relevant to CE, as well as on identifying and evaluating interventions based on these indicators. Employing a mixed-methods approach consisting of three studies (an interview study, a focus group study, and an online survey), the paper investigates the perspectives of three relevant stakeholders (learners, CE specialists, and educational technology specialists) by answering the following specific research questions:

- What indicators describing internal and external conditions do learners in CE perceive as relevant to their learning processes and outcomes and should, therefore, be considered by ALEs for CE?
- Based on these indicators, what interventions for personalizing and supporting learning processes do different stakeholders of ALEs for CE expect?
- How do different stakeholders of ALEs for CE evaluate these interventions in terms of learners' willingness to use the intervention, perceived learning support, as well as technological and organizational implementation effort?

1.3.2 Paper 2: Technology-Enhanced Personalized Learning Environments Based on Prior Knowledge in Continuing Education: An Experimental Study

Paper 2 evaluates the effectiveness of ALEs in the form of a technology-enhanced personalized learning environment based on prior knowledge (TEPLE-PK). TEPLEs-PK tailor learning activities to individual learners' prior knowledge, aiming at presenting the best next learning content to be learned by the individual learner in order to master a particular learning topic (Al-Chalabi et al., 2021; Chaipidech et al., 2022; Rasch & Middelbeck, 2022). The paper employs an experimental study with a between-subjects design to evaluate the effects of TEPLEs-PK on knowledge increase, learning path completion, and learner satisfaction in CE. Moreover, research has suggested that depending on their motivational dispositions, learners may benefit from different types of (personalized) learning support (Beheshitha et al., 2016; Lallé et al., 2016; Schumacher & Ifenthaler, 2018b). Therefore, the paper also investigates how learners' goal orientations and task value moderate the effects of TEPLEs-PK on learning outcomes. The paper addresses the following specific research questions:

- How do TEPLEs-PK (compared to non-personalized instruction) affect knowledge increase, learning path completion, and learner satisfaction in CE?
- How do learners' goal orientations and task value moderate the effects of TEPLEs-PK (compared to non-personalized instruction) on knowledge increase, learning path completion, and learner satisfaction in CE?

1.3.3 Paper 3: Self-Regulated Learning Strategies in Continuing Education: A Systematic Review and Meta-Analysis

Paper 3 aims to gather insights into the nature of SRL in CE. In general, effective SRL involves the use of SRL strategies, including cognitive (e.g., rehearsal), metacognitive (e.g., goal setting and planning), and resource management (e.g., time management) strategies (Pintrich et al., 1991, 1993; Winne, 2022; Zimmerman, 1990; Zimmerman & Pons, 1986). Therefore, the paper investigates the antecedents and outcomes of learners' use of SRL strategies in CE. The paper employs a systematic review to identify learning process-related, learner-related, CE-related, and work-related factors related to learners' use of SRL strategies in CE. Moreover, the paper employs a meta-analysis to investigate the strength and potential moderators of the underlying relationships. The following specific research questions are answered in Paper 3:

- What learning process-related, learner-related, CE-related, and work-related factors have been associated with learners' use of SRL strategies in empirical studies focusing on CE?
- To what extent are these factors related to learners' use of SRL strategies in CE?
- To what extent do methodological features (i.e., operationalization of variables) and the type of the CE activity (i.e., setting, work-relatedness, formality) moderate these relationships?

1.3.4 Paper 4: Personalization Is No Miracle Cure: Evaluation of a Technology-Enhanced Self-Regulated Learning Intervention in Continuing Education

Paper 4 aims to evaluate the potential of ALEs in supporting SRL in CE by implementing a technology-enhanced personalized SRL intervention (TEPSI) consisting of a goal-setting functionality, a personalized learning plan, and a personalized dashboard. The paper employs a mixed-methods approach. First, an experimental study with a between-subjects design was conducted to evaluate the effectiveness of the TEPSI by investigating its effects on learning path completion and learners' self-reported SRL strategies. Then, an interview study using the think-aloud method (Dillow, 1997; Konrad, 2020) was conducted to explore learners' perceived ease of use and usefulness of the TEPSI. Paper 4 addresses the following specific research questions:

- How does the availability of the TEPSI affect learning path completion and learners' self-reported SRL strategies in CE?
- How do learners' interactions with the TEPSI affect learning path completion and learners' self-reported SRL strategies in CE?
- How do learners in CE evaluate the ease of use of the TEPSI?
- How do learners in CE evaluate the usefulness of the TEPSI for supporting SRL?

1.4 Structure of This Thesis

The four research papers represent the core of this thesis and are presented and discussed in the following chapters. The next chapter (Chapter 2) introduces the general conceptual foundations underlying the four papers. It defines relevant concepts (CE, ALEs, SRL) and demonstrates the status quo of current research on ALEs and SRL in CE. The following four chapters (Chapters 3–6) present the four research papers in detail, covering their specific theoretical foundations, methodological approaches, findings, implications, and limitations. Finally, Chapter 7 summarizes the main findings of the four papers and derives theoretical and practical implications. In addition, the chapter outlines the general limitations of this thesis and its implications for future research, as well as includes a general conclusion.

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2. Conceptual Foundations

2.1 Continuing Education

2.1.1 Definition of Continuing Education

The term continuing education (CE; also referred to as further education) encompasses a wide variety of learning activities ranging from reading specialized literature to participating in structured educational programs that lead to a state-approved certificate (Demary et al., 2013; *Further and Higher Education Act*, 1992; Rosenkranz, 2022). CE serves the acquisition or renewal of knowledge (i.e., cognitive representations of learning content; Carter, 1985; Winterton et al., 2005), skills (i.e., abilities to perform a specific task; Attewell, 1990; Carter, 1985), and competences (i.e., knowledge, skills, behaviors, and attitudes necessary to be successful in a job or particular area; Le Deist & Winterton, 2005) and has usually been described as learning activities that take place after an initial phase of education (Demary et al., 2013; Deutscher Bildungsrat, 1970; Eurostat, 2024a). This initial phase of education occurs within formal educational systems, which are designed as consecutive educational pathways (e.g., K-12 education, professional apprenticeships, higher education) and may vary in length depending on the individual learner's educational pathway (Deutscher Bildungsrat, 1970; Eurostat, 2024a).

There is no clear and universally applicable definition of the end of an individual's initial phase of education, and thus, the possible starting point for CE is vague (Widany et al., 2017). Typically, based on the recommendation of the German Educational Council, the end of an individual's initial phase of education has been defined as an individual's entry into gainful employment (Bundesministerium für Bildung und Forschung [BMBF], 2024; Demary et al., 2013; Deutscher Bildungsrat, 1970; Eurostat, 2024a). However, this definition has been criticized for blurring the boundaries between CE and other areas of education (Widany et al., 2017). For example, would a higher education degree started after a period of gainful employment be considered CE or higher education? And what about learners who are employed while pursuing a professional apprenticeship or higher education degree (Gnahs & Reichart, 2014; Widany et al., 2017)? Moreover, since CE is not always related to the learner's job position, entry into gainful employment may not be a meaningful criterion (Demary et al., 2013; Rosenkranz, 2022). Hence, instead of specifying gainful employment as a precondition for CE, some definitions emphasize the age of the learners and the clear distinction between CE and other areas of education (BMBF, 2024; *Education Act*, 2022; *Further and Higher*

Education Act, 1992; Laal et al., 2014). For example, in the British Education Act, CE has been referred to as learning activities outside of secondary and higher education that are aimed at individuals above compulsory school age (*Education Act*, 2022; *Further and Higher Education Act*, 1992). Moreover, in recent surveys, CE has been operationalized as adult learning activities that do not fall within the scope of K-12 education, professional apprenticeships, or higher education (BMBF, 2024; Eurostat, 2024b).

In this thesis, CE is defined as learning activities that are distinct from K-12 education, professional apprenticeships, and higher education and that aim to develop or renew knowledge, skills, and competences after the completion of an initial phase of education (Demary et al., 2013; Eurostat, 2024a; *Further and Higher Education Act*, 1992). This initial phase of education typically ends with leaving secondary (e.g., K-12 education or professional apprenticeships) or higher education and may, but does not have to be, followed by gainful employment (Eurostat, 2024a; Gnahs & Reichart, 2014; Widany et al., 2017). Thus, according to this definition, individuals may participate in CE activities before entering gainful employment (BMBF, 2024; Schiersmann, 2007). Moreover, any learning activities related to K-12 education, professional apprenticeships, or higher education degrees are not considered CE, even if the learners have already entered gainful employment (*Education Act*, 2022; Widany et al., 2017).

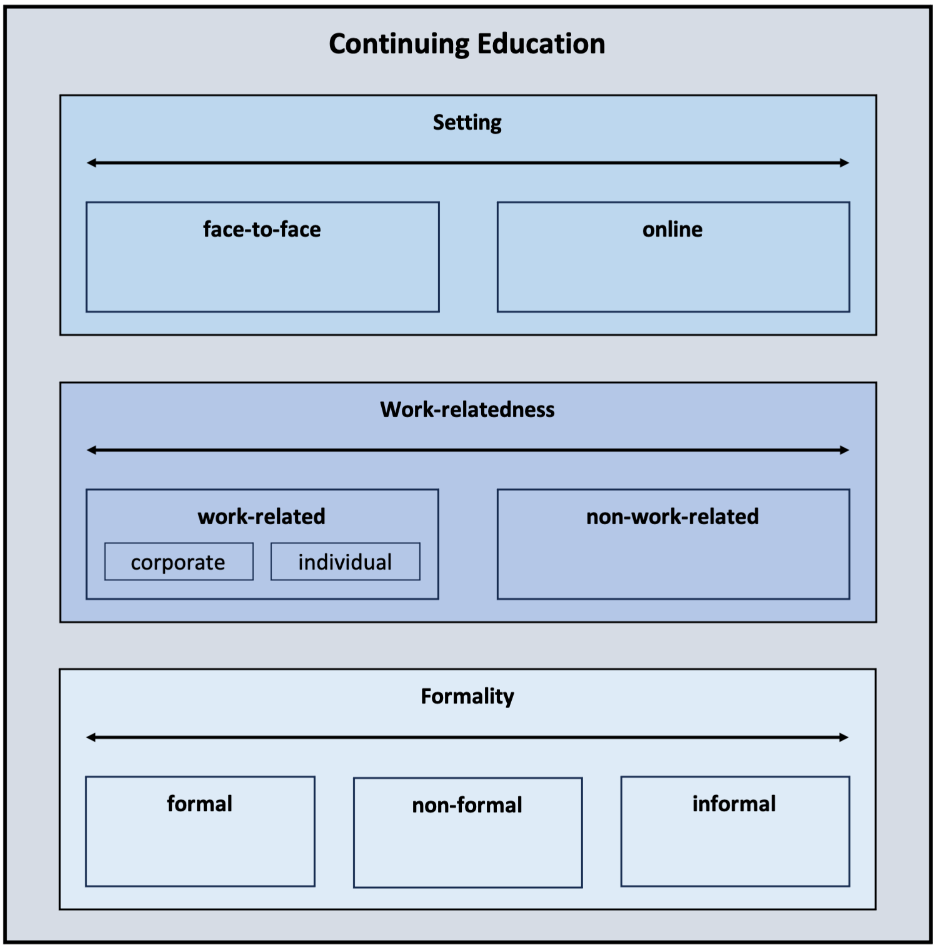
CE activities can be organized and delivered by different providers, including corporate providers (e.g., employers), public institutions (e.g., higher education institutions), (professional) associations (e.g., labor unions), and commercial providers (e.g., private educational institutions), or determined by the learners themselves (BMBF, 2024). Although in this thesis, CE is defined as being distinct from higher education, this does not mean that higher education institutions cannot be involved in the design of CE activities (BMBF, 2024; Widany et al., 2017). For example, higher education institutions may offer (scientific) CE activities in the form of Massive Open Online Courses (MOOCs) or professional certificate programs (Agyepong & Okyere, 2018; Weber, 2020; Wulf et al., 2014). Such CE activities typically differ from traditional higher education in that they do not lead to an undergraduate or consecutive graduate degree and have either no or special (e.g., professional experience) admission regulations. Moreover, they may be shorter in duration and less comprehensive (Heidelberg University, 2023; Versuti et al., 2020; Widany et al., 2017; Wulf et al., 2014).

2.1.2 Types of Continuing Education

To describe the variety of learning activities associated with CE, CE activities can be classified and arranged along the three dimensions of setting, work-relatedness, and formality (see Figure 2-1). CE activities can be delivered in face-to-face or online learning settings, or a combination of both (Widany, 2021). While initial approaches to CE were primarily (classroom-based) face-to-face learning activities requiring learners to be physically present at a certain location and time, CE activities delivered online have increased in the course of digitalization and have further been accelerated by the COVID-19 pandemic (BMBF, 2024; Ifenthaler, 2018; Keser Aschenberger et al., 2023). For example, synchronous and asynchronous online courses, online forums, and learning videos offer learning opportunities that are independent of location and sometimes time.

Figure 2-1

Overview of Different Types of Continuing Education



Further, CE can be work-related or non-work-related (Demary et al., 2013; Rosenkranz, 2022). Work-related CE (also referred to as professional development, workplace learning, or continuing vocational training; Eurostat, 2024b; Manuti et al., 2015; Mlambo et al., 2021) aims to develop or renew knowledge, skills, and competences that are relevant to the learner's current or future job position (Kyndt & Baert, 2013; Schiersmann, 2007). Typically, work-related CE serves the purpose of vocational retraining, adaptation to new work tasks and requirements, or career development (Rosenkranz, 2022). Conversely, non-work-related CE refers to learning activities that are not pursued for professional reasons and focus on knowledge, skills, and competences that are not directly linked to the learner's current or future job position (BMBF, 2024; Demary et al., 2013; Schiersmann, 2007).

Work-related CE can be further subdivided into corporate and individually motivated learning activities. Corporate work-related CE is financed at least partially by the learner's employer and takes place during paid working hours. On the contrary, individual work-related CE refers to learning activities that are pursued for professional reasons but are not financially supported by the employer and typically take place during leisure time (BMBF, 2024; Eurostat, 2024a; Rosenkranz, 2022; Schiersmann, 2007).

In addition, CE activities can be categorized into formal, non-formal, and informal CE. Formal CE refers to intended and organized learning activities that are regulated by law and may lead to a state-approved qualification certificate (Misko, 2008; Schumacher, 2018). Typical examples of formal CE include medical fellowships (French et al., 2022) and national upskilling programs, such as the German *Meister* and *Fachwirt* (Gnahs & Reichart, 2014). Formal CE activities are usually provided by accredited institutions and organized by certified educational staff who provide structures for learning (Gnahs & Reichart, 2014; Kawalilak & Groen, 2021). They are based on prescribed curricula that are oriented toward national qualification frameworks and may be embedded in a hierarchically structured educational system (Schiersmann, 2007; Schumacher, 2018).

Non-formal CE encompasses all intended and organized CE activities that are not regulated by law (Radcliffe & Colletta, 1989; Schumacher, 2018), such as MOOCs (Wulf et al., 2014), corporate management training programs (Gnahs & Reichart, 2014), or music lessons (BMBF, 2024). Similar to formal CE, non-formal CE includes structured learning activities, such as workshops, seminars, or lectures. However, unlike formal CE, these learning activities either lead to no qualification certificate at all or to a qualification certificate that is not state-approved (Eurostat, 2024a; Widany, 2021). Since they are not designed to adhere to national qualification frameworks, the curricula for non-formal CE activities are typically more flexible than those for formal CE activities and can be aligned more easily with the needs of the learners (Misko, 2008; Schumacher, 2018).

Informal CE refers to unorganized learning activities that occur through experiences in daily (work) life, such as reading specialized literature or learning through interactions with colleagues and friends (Eraut, 2004; Gnahs & Reichart, 2014). These learning activities are determined by the learner rather than external agents and do not occur in structured learning arrangements. They can be intentional, but they can also occur in situations in which learning is not the primary goal and occurs as a (sometimes unconscious) by-product (Eraut, 2004; Schiersmann, 2007; Schumacher, 2018).

The different types of CE activities arranged along the dimensions of setting, work-relatedness, and formality have been considered to overlap and should be viewed as a continuum rather than distinct categories (Eraut, 2004; Jurczyszyn, 2024; Schumacher, 2018; Widany, 2021). For instance, CE activities may be delivered in blended learning settings, including both face-to-face and online sessions, and they may be pursued for both work-related and non-work-related reasons (Widany, 2021). Further, the boundaries between formal, non-formal, and informal learning are blurred, and informal learning can also take place in formal and non-formal CE activities (Jurczyszyn, 2024; Schumacher, 2018).

2.2 Adaptive Learning Environments

2.2.1 Terms and Definitions: Adaptive vs. Personalized Learning

Adaptive learning is a vague concept that has not always been clearly distinguished from personalized learning. To date, there is no universal definition of the terms adaptive and personalized learning and no common agreement on their distinction (Hooshyar et al., 2024; Peng et al., 2019; Shemshack & Spector, 2020). Consequently, the two terms have been used interchangeably in many studies (Hooshyar et al., 2024; Xie et al., 2019). Some researchers have attempted to distinguish the two terms by defining adaptive learning as technology-enhanced personalized learning, that is, the realization of personalized learning through the use of educational technologies (Shemshack & Spector, 2020; Taylor et al., 2021). In this regard, personalized learning has been used as a more general term that describes learning environments in which learning activities are tailored to the individual learner. Personalized learning includes adjusting learning content and instructional approaches (referred to as differentiation) or the pace of learning (referred to as individualization) based on learner characteristics (Plass & Pawar, 2020a, 2020b; U.S. Department of Education, 2016; Walkington & Bernacki, 2020). Unlike adaptive learning, personalized learning does not necessarily involve educational technologies, as personalization can also be realized through instructors or the learners themselves (Fake & Dabbagh, 2020; Li & Wong, 2023). For example, instructors can provide personalized scaffolds (Van de Pol et al., 2010) or assign different learning tasks to different learners (Campbell et al., 2007). Learners can personalize their learning experiences by selecting learning materials or customizing features (e.g., avatars, background color) of the learning environment based on their preferences (Fake & Dabbagh, 2020; Plass & Pawar, 2020a). However, in large courses, it may be a challenging task for instructors to monitor the progress of each learner and personalize learning activities accordingly (Lee et al., 2018; Rachmad, 2022). Moreover, not all learners possess the necessary abilities to select and customize learning activities in a way that benefits learning (Raj & Renumol, 2018; Wozniak, 2020). This is where adaptive learning facilitated by educational technologies comes into play (Omar et al., 2024). Unlike personalization by instructors or learners, educational technologies enable the continuous collection and analysis of large amounts of information about learners and their contexts (Merino-Campos, 2025; Taylor et al., 2021). Thus, adaptive learning allows for the analysis of big data relating to a large number of learners, enables real-time and continuous adjustment of learning activities, and facilitates the consideration of not only static (e.g., personality traits) but also dynamic (e.g., learning performance) indicators for personalization that may change over time (e.g., Gligorea et al., 2023; Peng et al., 2019; Shemshack & Spector, 2020; Strielkowski et al., 2025; Xie et al., 2019). Hence, adaptive learning is closely linked to learning analytics, which refer to the collection and analysis of static and dynamic data about learners and learning contexts for real-time modeling, prediction, support, and optimization of learning processes (Ifenthaler, 2015; Ifenthaler & Yau, 2020; Wong & Li, 2020).

Aleven et al. (2017) pointed out that adaptive learning should go beyond the personalization of learning processes. Personalization involves adapting learning activities to differences between learners, such as varying levels of prior knowledge or different learning goals (Alonso et al., 2025; Plass & Pawar, 2020b). However, according to Aleven et al. (2017), adaptive learning environments (ALEs) should not only adapt to differences but also to similarities between learners, as the continuous collection of education-related data may enable the optimization of learning activities based on patterns that describe similarities between learners. For example, the presentation and explanation of specific learning content can be optimized based on common comprehension difficulties or errors in quiz questions demonstrated by several learners. Further, the difficulty level of learning materials can be adapted for all learners if they face similar challenges during the learning process. Taking into account this perspective, defining adaptive learning as the realization of personalized learning through educational technologies might not be sufficiently accurate (Aleven et al., 2017; Gligorea et al., 2023; Tasliarmut et al., 2025).

Aleven et al. (2017) distinguished three types of adaptive learning interventions: task-loop, step-loop, and design-loop interventions. Task-loop and step-loop interventions are based on individual learner differences and, thus, refer to personalized learning. In task-loop interventions, different learners are assigned different learning tasks (e.g., different learning content based on prior knowledge or individual learning goals; Hemmler et al., 2023; Rasch & Middelbeck, 2022). In step-loop interventions, all learners complete the same learning tasks, but specific features within these tasks vary based on individual learner differences (e.g., personalized feedback based on individual learning performance or dashboards that visualize specific indicators of individual learning behavior; Maier & Klotz, 2022; Park et al., 2023). In contrast, design-loop interventions refer to data-driven decisions made to optimize learning activities based on similarities between learners (e.g., adaptation of learning content explanations if learners demonstrate similar comprehension difficulties or errors in quiz questions) rather than individual learner differences and thus, do not include personalized learning (Aleven et al., 2017).

The conceptualization of adaptive learning used in this thesis combines the idea of adaptive learning as the realization of personalized learning through educational technologies (Shemshack & Spector, 2020; Taylor et al., 2021; Wang et al., 2024) with Aleven et al.'s (2017) three types of adaptive learning interventions. In this thesis, a learning environment is considered adaptive if it uses digital technologies to collect information about learners and their contexts and if it interactively responds to this information by adjusting its content and features to support learning processes (Gligorea et al., 2023; Plass & Pawar, 2020a; Strielkowski et al., 2025). Accordingly, ALEs include interventions for personalizing learning processes (i.e., task-loop and step-loop interventions) by tailoring learning activities to the individual learner, as well as design-loop interventions that adapt to similarities between learners (Aleven et al., 2017).

Figure 2-2 provides an overview of this thesis's conceptualization of adaptive and personalized learning. Adaptive learning overlaps with personalized learning in task-loop and step-loop interventions (Aleven et al., 2017; Alonso et al., 2025). In this thesis, personalized learning realized through instructors or learners is not considered adaptive learning (Taylor et al., 2021). However, adaptive learning does not exclude the agency of instructors and learners. For example, ALEs may provide visualizations, predictions, and recommendations based on learner data that may be used by instructors to optimize curricula or adapt teaching strategies (Curran et al., 2024; L. Lin et al., 2024). Further, ALEs may provide personalized dashboards assisting learners in self-regulating their learning processes (Park et al., 2023; Prasse et al., 2024) or recommend a range of different learning resources or strategies from which learners can select (Adam et al., 2024; Plass & Pawar, 2020b). In this regard, Plass and Pawar (2020a, 2020b) distinguished between adaptive and adaptable learning environments. They consider a learning environment adaptive if the interventions are delivered in a prescriptive way, while adaptable learning environments provide learners with various personalized options. Thus, in adaptable learning environments, the decision of what option to select is up to the learner, while in learning environments considered adaptive, this decision is up to the learning system. However, this distinction between adaptive and adaptable learning environments has not been used consistently across the literature, and most researchers have used the term adaptive regardless of whether the interventions were delivered in a prescriptive or non-prescriptive way (Adam et al., 2024; Plass & Pawar, 2020b). Therefore, in this thesis, the term adaptive learning includes both prescriptive and non-prescriptive interventions.

Figure 2-2

Adaptive Learning and Its Relation to Personalized Learning

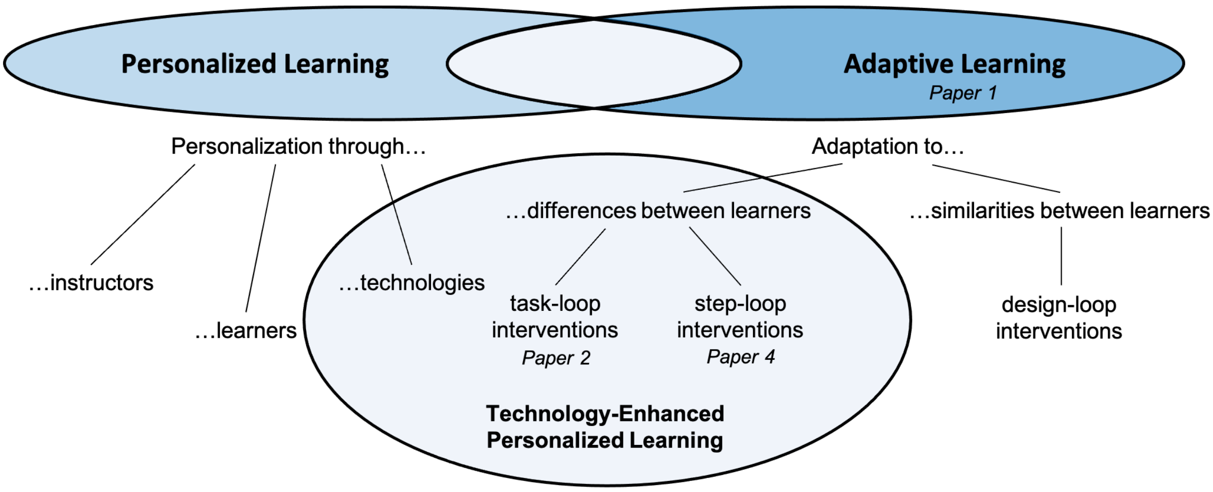


Figure 2-2 shows the areas of adaptive learning addressed by the papers of this thesis. Paper 1 ("Designing Adaptive Learning Environment for Continuing Education: Stakeholders' Perspectives on Indicators and Interventions") addresses the whole spectrum of adaptive learning, including task-loop, step-loop, and design-loop interventions. Paper 2 ("Technology-Enhanced Personalized learning Environments Based on Prior Knowledge in Continuing Education: An Experimental Study") evaluates a task-loop intervention tailoring learning content to individual learners' prior knowledge. Paper 4 ("Personalization is No Miracle Cure: Evaluation of a Technology-Enhanced Self-Regulated Learning Intervention for Continuing Education) evaluates a step-loop intervention aiming to support self-regulated learning (SRL) in CE. To highlight that Paper 2 and Paper 4 focus on personalized learning interventions and do not consider adaptivity based on similarities between learners, the term technology-enhanced personalized learning (instead of adaptive learning) is used to describe the interventions discussed in these papers. Since Paper 3 ("Self-Regulated Learning Strategies in Continuing Education: A Systematic Review and Meta-Analysis") focuses on the theoretical foundations of SRL in CE rather than adaptive learning, it has not been placed in Figure 2-2.

2.2.2 Adaptive Learning Environments for Continuing Education

Over the past decade, some researchers have introduced ALEs for CE (Bayly-Castaneda et al., 2024; Li & Wong, 2023). While design-loop interventions have largely been overlooked, researchers have developed task-loop and step-loop interventions for CE, such as personalized learning paths (e.g., Ilkou et al., 2021; Rasch & Middelbeck, 2022), recommender systems providing personalized suggestions of learning resources (e.g., Chaipidech et al., 2022; Rosen et al., 2018; Tavakoli et al., 2022), personalized dashboards (e.g., Davis et al., 2016; Goda et al., 2020; Pérez-Álvarez et al., 2020), as well as personalized feedback and prompts (e.g., Gabbay & Cohen, 2024; Khiat, 2022; Psathas et al., 2023). For example, Tavakoli et al. (2022) developed a recommender system for CE activities that provides personalized recommendations of skills and corresponding learning resources based on personal learning goals. A comparison of these recommendations with those of experts revealed that the system produced accurate recommendations of skills and high-quality learning resources. However, the researchers did not investigate how the recommender system affects learning processes. Rosen et al. (2018) developed a recommender system that provides personalized recommendations of learning materials based on individual learning performance in a MOOC. An experimental study revealed that the effectiveness of the recommender systems depended on the strategy used to generate recommendations. Specifically, recommending learning materials on topics with which individual learners are least familiar, based on their individual learning performance when interacting with learning content in the MOOC, can positively affect knowledge increase. However, the recommender system did not affect course completion rates.

Davis et al. (2016) developed a personalized dashboard providing visualizations of individual learning behavior (e.g., time spent on the platform, number of course videos watched) in a MOOC, as well as comparisons with the behavior of other learners. An experimental study revealed that the availability of the dashboard positively affected passing rates and course grades. However, these effects were small, and the vast majority of learners did not pass even if provided with the dashboard. Moreover, the dashboard had limited effects on learning engagement, affecting only two out of seven analyzed learning engagement dimensions. Further, Goda et al. (2020) introduced a support system for work-related CE that encourages learners to self-report on their daily work. The system uses these self-reports to automatically determine each learner's development level within the organization and to provide a dashboard that visualizes individual changes in that development level. The researchers assumed that the support system would support learners' self-reflection and help trainers and supervisors provide effective feedback, but they did not empirically evaluate the system.

Furthermore, recent advances in the field of generative artificial intelligence (AI) have created new opportunities for ALEs for CE (Ifelebuegu et al., 2023; Oubagine et al., 2025). Generative AI is a branch of AI that is capable of producing new content, such as texts, audios, or images, by learning from existing data (Banh & Strobel, 2023; Feuerriegel et al., 2024). For instance, generative AI tools may create learning materials tailored to learners' individual needs and provide immediate feedback on individual learning performance (Oubagine et al., 2025). Especially large language models (LLMs), which refer to a type of generative AI that can process and generate natural language (Shen et al., 2023), are currently receiving considerable attention in educational research (Oubagine et al., 2025; Sharma et al., 2025). According to Ifelebuegu et al. (2023), chatbots based on LLMs, such as ChatGPT, may act as virtual tutors available 24/7 for answering queries, offering explanations and examples, creating practice problems that help learners test their understanding, as well as monitoring progress and performance. However, when using LLMs for educational purposes, the potential drawbacks of these models need to be considered. These include algorithmic biases, hallucinations producing plausible-sounding but incorrect information, data privacy violations, and dishonest behavior when learners submit AI-generated assignments (Chandran, 2025; Ifelebuegu et al., 2023; Oubagine et al., 2025). Research has shown that effectively implementing LLMs to support learning processes in CE may be challenging (Gabbay & Cohen, 2024; X. Lin et al., 2024). For example, Gabbay and Cohen (2024) implemented ChatGPT to provide feedback on coding assignments in a MOOC on programming. Although ChatGPT effectively detected errors in learners' code, the feedback it produced tended to be inaccurate.

As mentioned in Chapter 1.2, research on ALEs for CE must be further advanced. Although researchers have introduced ALEs for CE (e.g., Davis et al., 2016; Tavakoli et al., 2022), robust empirical evidence is still missing. Several publications introducing ALEs for CE have focused on describing ALEs and their technological aspects rather than empirically evaluating their effects on learning (e.g., Goda et al., 2020; Tavakoli et al., 2022). While only a few researchers have conducted experimental studies to evaluate the effects of ALEs on learning processes and outcomes in CE, these studies have focused on very specific interventions (e.g., personalized recommendations of learning materials based on individual learning performance, personalized dashboard visualizing individual learning behavior in a MOOC; Davis et al., 2016; Rosen et al., 2018) and have not covered the whole spectrum of possible interventions of ALEs (Komalawardhana & Panjaburee, 2024; Li & Wong, 2023). Moreover, it remains unclear whether and which individual and contextual factors determine the effectiveness of ALEs in supporting learning processes in CE. Therefore, further empirical studies are needed to evaluate the effects of ALEs on learning processes and outcomes in CE, as well as to provide empirical guidance for designing ALEs for CE (Kaliisa et al., 2022; Li & Wong, 2023; Plass & Pawar, 2020b).

2.3 Self-Regulated Learning

2.3.1 Definition and Theories of Self-Regulated Learning

SRL can be defined as active and dynamic processes whereby learners monitor and control their cognitive, affective, and behavioral activities during learning to achieve personal learning goals (Pintrich, 2000; Zimmerman & Schunk, 2011). Learners' abilities to successfully engage in SRL have been considered an important predictor of learning success, especially in learning environments with limited regulation by external entities, such as instructors or prescribed curricula, that provide guidance for learning (Broadbent & Poon, 2015; Guntur & Purnomo, 2024; Sitzmann & Ely, 2011). Over the past 50 years, researchers have developed several theories of SRL, mainly focusing on K-12 and higher education (for a comprehensive review, see Panadero, 2017). These theories highlight different aspects and sub-processes of SRL, but they share some basic assumptions (Panadero, 2017; Pintrich, 2000).

For example, SRL theories agree that learners are active and constructive participants in their learning process and potentially able to monitor and control certain aspects of their learning experiences, such as their cognitions and affects (Pintrich, 2000; Zimmerman & Schunk, 2011). Moreover, SRL has been considered to involve a set of goals or standards against which learners compare their learning performance to decide whether they need to adjust their learning behavior and strategies (Pintrich, 2000; Puustinen & Pulkkinen, 2001; Winne, 2011; Winne & Hadwin, 1998). Further, several SRL theories assume that SRL is shaped by personal (e.g., motivational dispositions, personality traits) and contextual (e.g., task conditions, time) characteristics (Järvelä & Hadwin, 2013; Pintrich, 2000; Winne, 2022; Winne & Hadwin, 1998; Zimmerman, 2000). For instance, according to Winne (2022), personal and contextual characteristics influence how learners operate on information resources and what standards they choose to evaluate their learning performance.

In addition, several researchers have suggested that SRL is cyclical in nature and consists of different recurring phases (Panadero, 2017; Puustinen & Pulkkinen, 2001). Although the labeling and number of phases and related sub-processes differ between SRL theories (Pintrich, 2000; Winne, 2011; Winne & Hadwin, 1998; Zimmerman, 2000, 2013), they may be arranged around Zimmerman's (2000) three phases forethought, performance, and self-reflection (Panadero, 2017). In the *forethought phase*, learners prepare for their learning efforts. They analyze the learning task, set learning goals, plan how to approach these goals, and activate their motivational energies for learning. In the *performance phase*, learners execute the learning task and the plan they created beforehand while continuously monitoring and controlling their learning progress. Finally, in the *self-reflection phase*, learners evaluate their learning performance in relation to their previously set learning goals and make attributions to explain their success or failure. These self-reflections may influence subsequent forethought phases and, thus, complete the self-regulatory cycle (Panadero, 2017; Zimmerman, 2000, 2013).

Finally, several SRL theories assume that successful self-regulators are characterized by their effective use of SRL strategies in each phase of the self-regulatory cycle (Fontana et al., 2015; Pintrich et al., 1993; Winne, 2011, 2022; Zimmerman, 1990). SRL strategies refer to actions and processes directed at acquiring information or regulating internal and external resources (Pintrich et al., 1993; Zimmerman, 1990, 2013). SRL theories have proposed slightly different SRL strategies, which focus on different aspects of self-regulation. For example, Zimmerman and Pons (1986) identified 15 SRL strategies (e.g., goal setting and planning, environmental structuring) that distinguish high-performing from low-performing learners and consider cognitive, metacognitive, motivational, and contextual aspects of SRL. Winne and Hadwin (1998) primarily emphasized cognitive and metacognitive aspects of SRL and proposed five types of operations (searching, assembling, rehearsing, and translating) that learners employ to process information resources. According to Pintrich et al. (1991, 1993), SRL strategies can be classified into cognitive, metacognitive, and resource management strategies. *Cognitive strategies* (e.g., rehearsal, elaboration) facilitate the processing of information from learning materials (Pintrich et al., 1991, 1993; Wild & Schiefele, 1994; Winne, 2011). *Metacognitive strategies* (e.g., goal setting and planning, self-monitoring) refer to second-order cognitions that help learners monitor and control their cognition and application of cognitive strategies (Pintrich et al., 1991, 1993; Theobald, 2021). *Resource management strategies* (e.g., time management, effort regulation) involve strategies for regulating other internal and external resources besides cognition, such as effort, time, or the study environment (Pintrich, 1999; Pintrich et al., 1991, 1993; Theobald, 2021).

This thesis focuses on the antecedents and outcomes of different SRL strategies in CE, as well as how learners' use of SRL strategies may be supported in CE. While reviewing SRL strategies from different works and theories, Pintrich et al.'s (1991, 1993) classification into cognitive, metacognitive, and resource management strategies is used to group these strategies. As such, the relevance and effects of different SRL strategies can be investigated systematically, and appropriate interventions to support SRL in CE can be developed (Theobald, 2021; Xu et al., 2023).

2.3.2 Self-Regulated Learning in Continuing Education

Although researchers have emphasized the importance of SRL in CE (e.g., Chaker & Impedovo, 2021; Teich et al., 2024), SRL theories focusing on CE are missing (Cuyvers et al., 2020; Panadero, 2017). Since learning in CE differs from learning in other educational contexts, such as K-12 and higher education (Knowles et al., 2012; Tynjälä, 2008; Wozniak, 2020), and since SRL has been considered context-dependent (Pintrich, 2000; Winne, 2022), SRL in CE may differ from SRL in other contexts (Cuyvers et al., 2020; Onah et al., 2024). Thus, designing effective learning experiences for CE requires an in-depth investigation that goes beyond existing SRL theories focusing on K-12 and higher education (e.g., Pintrich, 2000; Zimmerman, 2000). It is necessary to examine how learners in CE specifically self-regulate their learning processes and apply SRL strategies (Cuyvers et al., 2020; Panadero, 2017).

Since learners in CE are often granted a high degree of autonomy to decide when, how, and what they would like to learn (Sitzmann & Ely, 2011), and since they typically have to balance learning with other commitments (e.g., work, family; Eriksson et al., 2017; Schröer et al., 2022), researchers have particularly emphasized the importance of metacognitive and resource management strategies for CE (Alonso-Mencía et al., 2020; Teich et al., 2024). For example, metacognitive strategies, such as goal setting, planning, and self-monitoring, have been considered essential for focusing on relevant learning resources, developing a realistic study agenda to achieve short- and long-term goals, and tracking learning progress in autonomous and flexible CE activities (Handoko et al., 2019; Nguyen et al., 2024; Teich et al., 2024). Further, resource management strategies, such as time management, environmental structuring, and effort regulation, may help learners allocate time for learning, organize a distraction-free study space, as well as manage their motivation and competing demands from other commitments (Nawrot & Doucet, 2014; Pintrich et al., 1991; Teich et al., 2024).

However, since CE can occur through a variety of different learning activities (Rosenkranz, 2022; Schiersmann, 2007), SRL may unfold differently depending on the type of CE. For example, SRL may be more important in online than in face-to-face CE activities due to the absence of fixed teaching times and locations, as well as the reduced presence of instructors (Broadbent & Poon, 2015; Guntur & Purnomo, 2024). Further, although CE has been characterized by high learner autonomy (Sitzmann & Ely, 2011), corporate work-related CE may be externally regulated by the employer (Hemmler et al., 2023). For instance, employers may prescribe mandatory CE activities that need to be completed by a certain date (de Jong et al., 2025). Compared to non-work-related CE, which is typically self-directed and voluntary, these CE activities may provide learners with fewer possibilities to self-regulate their learning (Hemmler et al., 2023). Moreover, SRL might play a more important role in informal CE than in formal and non-formal CE due to the unstructured and unorganized nature of informal learning (Beishuizen & Steffens, 2011).

Some researchers have attempted to study SRL in the context of CE. For example, systematic reviews have examined methods for measuring and supporting SRL in MOOCs (Cerón et al., 2020; Lee et al., 2019). Further, Fontana et al. (2015) and Margaryan et al. (2022) developed questionnaires for studying SRL strategies in work-related CE. Nguyen et al. (2024) examined the perceived SRL challenges and support needs of learners in CE, revealing that learners in CE often struggle to set appropriate learning goals, successfully plan and monitor their learning progress, evaluate and adapt their learning behavior, and manage their time and motivation effectively. Mitschelen and Kauffeld (2025) studied learners' use of SRL strategies during organizational onboarding, showing that effective SRL strategies help learners transform formal and informal CE activities into meaningful onboarding experiences. However, despite these research efforts on SRL in CE, comprehensive analyses of how SRL unfolds in different types of CE are missing. The range of factors triggering and inhibiting learners' use of SRL strategies, as well as the most relevant SRL strategies in different types of CE, remain unclear.

2.3.3 Supporting Self-Regulated Learning Through Adaptive Learning Environments in Continuing Education

In the past decade, a branch of research has emerged linking ALEs with SRL (Prasse et al., 2024; Viberg et al., 2020). ALEs have been considered beneficial for providing timely and personalized support for SRL (Nguyen et al., 2024; Teich et al., 2024). Despite the lack of theoretical grounding on SRL in CE, researchers have introduced ALEs to develop technology-enhanced personalized SRL interventions (TEPSIs), such as dashboards (e.g., Davis et al., 2016; Pérez-Álvarez et al., 2020), digital prompts (Khiat, 2022; Psathas et al., 2023), and recommendations of learning partners (Milikić et al., 2020) or learning content (Teich et al., 2024). For example, Psathas et al. (2023) developed a personalized dashboard to support SRL during collaborative learning activities in a MOOC, along with e-mail prompts to promote learners' use of the dashboard. The researchers investigated three experimental conditions, all of which had access to the dashboard but received different e-mail prompts: (1) a general intervention condition in which learners received non-personalized prompts with recommendations on how to interpret the dashboard visualizations, (2) a personalized intervention condition in which learners additionally received personalized feedback and specific recommendations on how to strengthen specific skills visualized in the dashboard, and (3) a control condition in which learners were only informed about the existence of the dashboard. Despite the dashboard and prompts being designed to support SRL, learners' use of SRL strategies decreased in all three conditions over time. Nevertheless, the decrease was smaller in the personalized intervention condition than in the control condition, though it did not differ between the personalized intervention condition and the general intervention condition.

Teich et al. (2024) studied SRL in the context of a work-related online course and developed a TEPSI consisting of three components: (1) a structured course overview organizing content modules by topic and media type, (2) personalized estimations of the learning time needed to complete each content module based on learners' answers in a pre-questionnaire about their prior knowledge and experiences, and (3) personalized highlighting of recommended learning content based on learners' prior knowledge. Learners in the intervention condition, who had access to the TEPSI, demonstrated superior environmental structuring (i.e., strategies for organizing a quiet study environment that is free of distractions; Pintrich et al., 1991, 1993) compared to those in the control condition, who did not have access to the TEPSI. However, the two conditions did not differ in other SRL strategies, and only 14 out of 36 learners in the intervention condition frequently engaged with the TEPSI. These findings align with other studies showing limited learner engagement with TEPSIs in CE (Cobos, 2023; Pérez-Álvarez et al., 2020).

Further, Khiat (2022) introduced a TEPSI aiming to support time management in an online course for healthcare professionals. The TEPSI provided learners with a recommended study schedule to help them complete the course within the intended timeframe and released learning materials adaptively so that learners could access new topics only after completing the prerequisites. In addition, learners received personalized e-mail prompts with feedback on their time management and learning progress. The availability of the TEPSI positively affected learners' time management but did not target other SRL strategies. Moreover, the study was subject to some methodological limitations. For example, the analyses included only n = 9 learners in the control condition, and learners were not randomized into the intervention and control conditions, which limits causal conclusions.

Hence, although researchers have introduced TESPIs for CE, these interventions still face challenges in effectively supporting SRL. The limited impact on learners' use of SRL strategies (e.g., Psathas et al., 2023), the addressing of only isolated SRL strategies (e.g., Khiat, 2022), the lack of learner engagement (e.g., Teich et al., 2024), and methodological limitations (e.g., Khiat, 2022) constrain the empirical evidence for ALEs aiming to support SRL in CE. Further research is needed to design and implement ALEs that provide effective support for SRL in CE, as well as to evaluate their potential benefits and weaknesses.

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3. Paper 1: Designing Adaptive Learning Environments for Continuing Education: Stakeholders' Perspectives on Indicators and Interventions

3.1 Introduction

Continuing education (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 the completion of an initial phase of education (e.g., after the completion of a university degree; Demary et al., 2013; *Further and Higher Education Act*, 1992; Schiersmann, 2007). Due to rapid societal changes, such as digitalization and globalization, the need for CE has never been greater than it is today. Individuals must constantly acquire new knowledge, skills, and competences to meet new challenges and to keep pace in today's rapidly changing (working) world (Kittel et al., 2021; Omar et al., 2024; Rasch & Middelbeck, 2022).

Learners in CE are usually heterogeneous in terms of their (professional) backgrounds and experiences and, therefore, may come into a CE activity with different prerequisites and expectations (e.g., different levels of prior knowledge regarding the course topic, different learning strategies and interests; Knowles et al., 2012; Meister & Willyerd, 2021; Rasch & Middelbeck, 2022). Whereas a common assumption is that learning is more effective when it is adapted to individual learner differences (Aleven et al., 2017; Dockterman, 2018; Omar et al., 2024), designing personalized learning environments that meet learners' individual prerequisites and expectations remains a major challenge for CE (Fake & Dabbagh, 2020; Omar et al., 2024; Rasch & Middelbeck, 2022).

Recent research on educational technologies has recognized the potential of adaptive learning environments (ALEs) for supporting personalized learning (e.g., Gligorea et al., 2023; Omar et al., 2024). ALEs are digital learning systems that analyze data about learners and their contexts to tailor learning activities (e.g., learning content, instructional approaches) to the individual learner and to support learning processes (Hemmler & Ifenthaler, 2022b; Plass & Pawar, 2020a; Xie et al., 2019). Whereas empirical studies have demonstrated the potential of ALEs for enhancing learning success in higher education (Zheng et al., 2022), ALEs have been rarely researched in the field of CE (Bernacki et al., 2021; Li & Wong, 2023; Xie et al., 2019). Although researchers have emphasized the benefits of ALEs for personalizing and supporting learning processes in CE (Fan & Jiang, 2021; Omar et al., 2024), empirical studies investigating and evaluating ALEs in the context of CE are scarce (Bernacki et al., 2021; Li & Wong, 2023). Consequently, empirically-based frameworks for designing ALEs for CE are missing (Bernacki et al., 2021; Li & Wong, 2023; Xie et al., 2019). For example, what indicators (i.e., what information about learners and their contexts) should be collected by ALEs for CE in order to adapt learning activities efficiently? Further, what interventions for personalizing and supporting learning processes in CE should be derived based on specific indicators? These questions have been considered central to the design of ALEs and yet need to be answered (Aleven et al., 2017; Li & Wong, 2023; Plass & Pawar, 2020b).

To identify reliable and meaningful indicators and interventions for ALEs for CE, a solid investigation of how learners perceive learning processes in CE and what learners, CE specialists, and educational technology specialists expect from ALEs is crucial (Plass & Pawar, 2020a; Schumacher & Ifenthaler, 2018). Without considering the perceptions and expectations of these stakeholders, the implementation of ALEs in CE might fail (Fake & Dabbagh, 2020; Gligorea et al., 2023; Gril et al., 2022; Schumacher & Ifenthaler, 2018). For example, ALEs might not meet learners' specific needs (Gril et al., 2022), learners might feel observed and manipulated by the continuous collection and analysis of data (Tsai et al., 2018), or they might feel a loss of autonomy in their learning processes, which could impair intrinsic motivation (Deci et al., 1996; Schumacher & Ifenthaler, 2018). Further, CE and educational technology specialists might fail to implement ALEs in practice if technological or organizational challenges (e.g., privacy regulations, lack of technological resources) are ignored during the design phase (Fake & Dabbagh, 2020; Gligorea et al., 2023; Tsai et al., 2018).

Therefore, this paper aims to investigate different stakeholders' (i.e., learners', CE specialists', and educational technology specialists') perspectives on ALEs for CE as well as to develop a framework of indicators and interventions for ALEs for CE. Such a framework may help researchers, system designers, as well as CE and educational technology specialists select appropriate indicators and interventions to develop and implement ALEs for CE. The paper adopts a mixed-methods approach consisting of three studies. We first conducted a qualitative interview study to identify indicators that should be collected and analyzed by ALEs for CE. Subsequently, we conducted qualitative focus group interviews and a quantitative online survey to specify and evaluate possible interventions for personalizing and supporting learning processes based on these indicators.

3.2 Continuing Education

The term CE encompasses a broad variety of learning activities that can be formal (i.e., organized learning activities that are regulated by law and may lead to a state-approved certificate; Misko, 2008; Schumacher, 2018), non-formal (i.e., organized learning activities that are not regulated by law; Radcliffe & Colletta, 1989; Schumacher, 2018), or informal (i.e., unorganized and sometimes unconscious and unintended learning activities that occur through experiences in daily life; Eraut, 2004; Schiersmann, 2007; Schumacher, 2018). Moreover, CE can be work-related or non-work-related, depending on whether the CE activity is relevant to the learner's job position (Demary et al., 2013; *Further and Higher Education Act*, 1992).

While early approaches to CE were primarily (classroom-based) face-to-face learning activities, CE activities delivered online have increased in the past decade (Ifenthaler, 2018; Keser Aschenberger et al., 2023; Şahin et al., 2021). For example, formal and non-formal CE have been realized through synchronous, asynchronous, and self-paced online courses (Meyer et al., 2023), whereas online forums, social media, and knowledge-sharing platforms may provide opportunities for informal CE (Meyer et al., 2023; Schumacher, 2018).

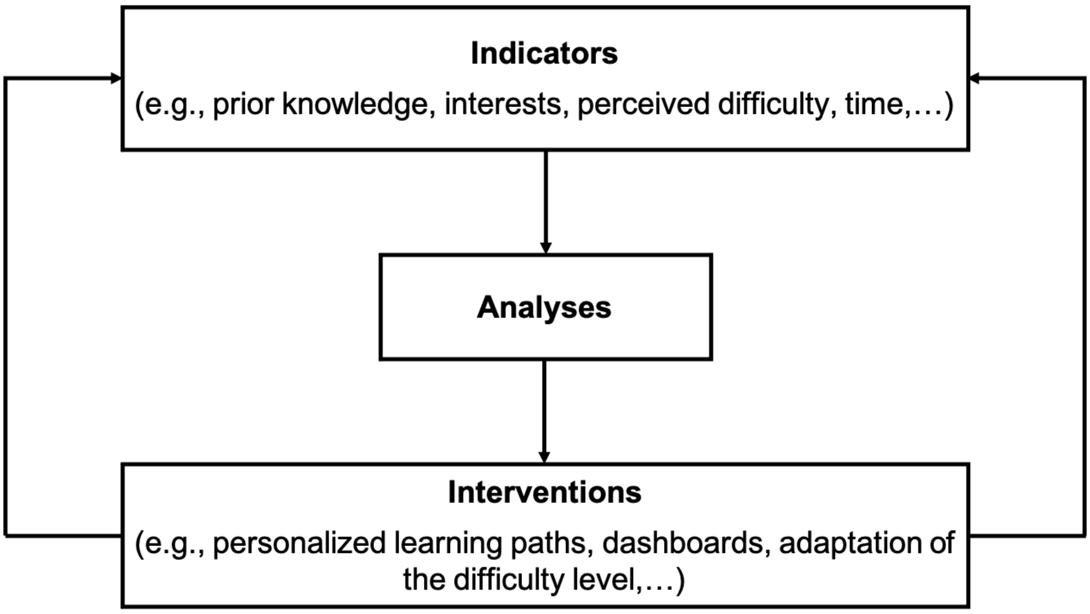
In contrast to traditional face-to-face learning activities, online CE may provide access to learning opportunities for a wide range of learners, regardless of time and place (Ifenthaler, 2018; Meyer et al., 2023). However, research has shown that the immense number of learning resources and CE activities offered online may challenge learners (as well as learning and development managers in business organizations) to find the learning activity that best meets individual prerequisites and expectations (Eriksson et al., 2017; Wu et al., 2020). Moreover, online CE following a one-size-fits-all approach that ignores learners' individual differences may suffer from high dropout rates and impaired learning performance (Wang et al., 2023; Xiao & Hew, 2024). Hence, researchers have recently recognized that these challenges of online CE may be overcome through the development of ALEs (Hemmler et al., 2023; Rasch & Middelbeck, 2022; Xiao & Hew, 2024). Educational technologies employed for online learning enable the analysis of large amounts of education-related data that may provide useful insight into learning behavior and can be leveraged to personalize and support learning processes (Gligorea et al., 2023; Zawacki-Richter et al., 2019; Zheng et al., 2022).

3.3 Adaptive Learning Environments

Figure 3-1 provides an overview of the functionalities of ALEs: ALEs collect indicators (e.g., prior knowledge, interests). Indicators are specific variables that provide information about learners and their contexts and that are analyzed (e.g., using statistical or artificial intelligence-based methods) to develop appropriate interventions for personalizing and supporting learning processes (Ifenthaler & Widanapathirana, 2014; Plass & Pawar, 2020b; Yau & Ifenthaler, 2020). These interventions may, for example, include personalized learning content and learning paths (Rasch & Middelbeck, 2022; Xue-jun et al., 2021), personalized user interfaces and dashboards (Liu et al., 2003; Park et al., 2023), personalized time schedules and learning paces (Pérez-Álvarez et al., 2020; Yau & Joy, 2008), personalized recommendations of courses, learning activities, and partners for peer learning (Milikić et al., 2020; Siadaty et al., 2016; Tavakoli et al., 2022), or personalized feedback and prompts (Mejeh et al., 2024; Strauß & Rummel, 2021). These interventions can either be delivered in a non-prescriptive way, providing learners with various individualized options to select (sometimes also referred to as *adaptable* learning environments), or in a prescriptive way, where one option is delivered automatically, leaving no choice to the learner (Plass & Pawar, 2020a, 2020b).

Figure 3-1

Adaptive Learning Environments (Adapted From Yau & Ifenthaler, 2020)



Further, Aleven et al. (2017) stated that ALEs should not only include interventions for personalizing learning processes but also interventions tailored to similarities between learners. For example, if all learners' test results show that the learning activities might have missed one of the instructional objectives defined by the course designer, the learning activities should be updated in their next iteration. Further, if learning activities are generally perceived as too difficult, the difficulty level may be adapted for all learners. Thus, while adaptive learning has often been used as a synonym for personalized learning (Bernacki et al., 2021; Xie et al., 2019), Aleven et al. (2017) proposed an additional type of adaptivity: adaptivity based on similarities rather than differences between learners. In this regard, Aleven et al. (2017) distinguished between three types of interventions for ALEs: task-loop, step-loop, and design-loop interventions. In task-loop interventions, different learners are given different learning tasks based on the diagnosis of individual learner differences (e.g., personalized learning paths based on learners' individual prior knowledge; Rasch & Middelbeck, 2022). In step-loop interventions, all learners complete the same learning tasks, but specific features within these tasks vary based on individual learner differences (e.g., personalized feedback, personalized dashboards; Mejeh et al., 2024; Park et al., 2023). Design-loop interventions refer to decisions made to interactively respond to similarities between learners (e.g., adaptation of the difficulty level if the course is generally perceived as too difficult; Aleven et al., 2017).

3.4 Adaptive Learning Environments for Continuing Education

Although research on ALEs for CE is still far from being comprehensive (Bernacki et al., 2021; Li & Wong, 2023), a few researchers have begun to develop ALEs for CE. For example, some researchers have introduced personalized dashboards that visualize specific indicators of learning behavior to support self-regulated learning (SRL; Davis et al., 2016; Pérez-Álvarez et al., 2020). Other researchers have developed recommender systems that provide personalized recommendations of learning resources and content (Chaipidech et al., 2022; Tavakoli et al., 2020, 2022; Xue-jun et al., 2021), skills and competences (Siadaty et al., 2016; Tavakoli et al., 2022), or learning paths (Ilkou et al., 2021). González-Castro et al. (2021) developed an adaptive learning module in which the difficulty of quiz questions is continuously adjusted, and personalized recommendations of learning videos are provided based on learners' performance in previous quiz questions. Further, Rasch and Middelbeck (2022) introduced a learning platform that offers personalized learning paths based on learners' individual level of prior knowledge.

However, robust empirical evidence regarding the effectiveness of ALEs in supporting learning processes in CE is still lacking (Bernacki et al., 2021; Li & Wong, 2023). While a recent meta-analysis revealed positive effects of ALEs on learning achievement in K-12 and higher education (Zheng et al., 2022), experimental studies evaluating ALEs for CE are scarce (Bernacki et al., 2021; Li & Wong, 2023; Viberg et al., 2020). Moreover, unified agreements on the critical components of ALEs, such as indicators or interventions, are still missing (Bernacki et al., 2021; Plass & Pawar, 2020b). Most existing ALEs are not aligned with learning theories or findings from empirical studies, so the selection of indicators and interventions remains nebulous (Bernacki et al., 2021; Yau & Ifenthaler, 2020). A user-centered and empirically-based framework for selecting indicators and interventions can provide guidance for developing explainable and trustworthy ALEs as well as systematically test the underlying assumptions about how ALEs can address learners' individual needs and influence learning outcomes (Bernacki et al., 2021; Omar et al., 2024; Plass & Pawar, 2020b).

3.4.1 Indicators

Reliable indicators are crucial for ALEs, as accurate information about learners and their contexts is needed to derive adequate interventions to personalize and support learning processes (Gašević et al., 2016; Gril et al., 2022; Ifenthaler & Yau, 2020). Early approaches to developing ALEs have mainly concentrated on data-driven analytics using readily available indicators, such as indicators automatically collected by the learning environment (e.g., login frequency, video usage; Ifenthaler & Yau, 2020). However, it remains unclear whether these indicators really reflect relevant learning behavior, what theoretical constructs (e.g., motivation, self-regulation) are reflected by these indicators, and how these indicators can serve as an information basis for possible interventions (Kaliisa et al., 2022; Yau & Ifenthaler, 2020). Consequently, the translation of indicators into adequate interventions has been considered a main challenge in designing ALEs (Ifenthaler & Yau, 2020; Kaliisa et al., 2022). Therefore, current research has suggested that the search for indicators requires more theoretical and empirical answers, as learning theories and findings from empirical studies can explain fundamental mechanisms of learning and help design pedagogically meaningful interventions (Giannakos & Cukurova, 2023; Omar et al., 2024; Plass & Pawar, 2020b). Researchers have argued that only indicators relevant to achieving desired learning processes and outcomes should be considered for ALEs (Aleven et al., 2017; Plass & Pawar, 2020b). In addition, sufficient theoretical or empirical knowledge of these indicators should be available to design adequate interventions (Omar et al., 2024; Plass & Pawar, 2020b).

Thus, a solid investigation of learning processes in CE is necessary to identify reliable indicators for ALEs for CE. It needs to be studied how learners perceive their learning processes, what challenges they face, and what indicators they perceive as most relevant to supporting their learning processes (Omar et al., 2024; Schumacher & Ifenthaler, 2018). Existing ALEs for CE have focused on trace data indicators (e.g., number of videos watched, time spent on course content; Davis et al., 2016; Pérez-Álvarez et al., 2020), learning goals (e.g., Tavakoli et al., 2022), prior knowledge (e.g., Rasch & Middelbeck, 2022; Xue-jun et al., 2021), or learning styles (e.g., Chaipidech et al., 2022; Xue-jun et al., 2021). However, a clear theoretical or empirical rationale for these indicators is missing. It remains unclear why these indicators have been preferred over other indicators and what other indicators might be considered by ALEs for CE.

In a recent systematic review, Hemmler and Ifenthaler (2022a) identified more than 200 indicators that have been associated with learning processes and outcomes (e.g., learning performance, learner satisfaction) in recent empirical studies across different educational contexts. These indicators included indicators related to internal and external conditions of learning. Internal conditions (e.g., personality, emotions) describe learners' personal and subjectively perceived learning experiences, dispositions, and beliefs. External conditions (e.g., course characteristics, characteristics of the learning materials) describe objective and predefined characteristics of the learning context (Greene & Azevedo, 2007; Winne, 2022; Winne & Hadwin, 1998). The findings of Hemmler and Ifenthaler's (2022a) systematic review are supported by several learning theories, such as Tynjälä's (2013) 3P-model of workplace learning or Winne and Hadwin's (1998) theory of SRL, suggesting that both internal and external conditions influence learning processes and outcomes (Greene & Azevedo, 2007; Tynjälä, 2013; Winne, 2022; Winne & Hadwin, 1998). Consequently, due to their impact on learning, researchers have argued that internal and external conditions relevant to a specific learning situation should be considered as indicators for ALEs (Gašević et al., 2015, 2016; Hemmler & Ifenthaler, 2022a).

Hemmler and Ifenthaler's (2022a) systematic review may serve as a useful basis for identifying indicators for ALEs. However, there are at least three reasons why the systematic review needs to be complemented by further research in order to develop a valid framework of indicators for ALEs for CE. First, the systematic review did not focus on CE exclusively, and the majority of the included studies focused on higher education. Higher education differs from CE (Knowles et al., 2012; Tynjälä, 2013). For example, while learning is the main occupation of full-time higher education students, learners in CE usually have to balance learning with more concurrent commitments (e.g., family or professional commitments) and may have limited time available for learning (Nawrot & Doucet, 2014; Schröer et al., 2022). Therefore, the relevance of specific indicators may differ between CE and higher education. Second, Hemmler and Ifenthaler's (2022a) systematic review did not focus on online learning exclusively. Therefore, it remains unclear which of the identified indicators are most relevant to online learning settings. Since ALEs are usually realized in online learning settings, and since conditions in online learning settings may differ from face-to-face learning activities (e.g., regarding learner autonomy and flexibility; Broadbent & Poon, 2015; Plass & Pawar, 2020a), indicators impacting learning processes and outcomes in online learning settings need to be investigated. Third, the systematic review did not investigate learners' perceptions of different indicators. Thus, it remains unclear whether the indicators identified by Hemmler and Ifenthaler (2022a) reflect learners' specific needs and subjective experiences. Therefore, we conducted an interview study to investigate the perceptions and learning experiences of learners in online CE and to identify indicators for ALEs for CE.

3.4.2 Interventions

Existing research on ALEs for CE has introduced task-loop and step-loop interventions such as recommender systems (Tavakoli et al., 2022), personalized learning paths (Rasch & Middelbeck, 2022), and dashboards (Pérez-Álvarez et al., 2020). However, as discussed in Section 3.4.1, these interventions were based on indicators with missing theoretical or empirical rationale. Moreover, relevant stakeholders' perspectives on these interventions have largely been ignored. So far, it remains unclear what interventions learners in CE expect from ALEs and what interventions CE specialists and educational technology specialists consider useful and feasible for CE.

In their interview study, Schumacher and Ifenthaler (2018) identified several interventions for personalizing and supporting learning processes in higher education (e.g., recommendation of learning partners, prompts for self-assessment). In a follow-up study (Schumacher et al., 2019), these interventions were evaluated by experts in terms of students' willingness to use the intervention, students' perceived learning support, as well as technological and organizational implementation effort. The findings of this follow-up study show that interventions that are positively perceived in terms of willingness to use and learning support do not necessarily have a low implementation effort and vice versa (Schumacher et al., 2019). Therefore, not only learners' perspectives on interventions but also technological and organizational challenges need to be considered when designing ALEs.

A similar study identifying and evaluating interventions for ALEs for CE does not exist so far. Since learners' conditions (e.g., family and professional commitments, time available for learning) in CE may differ from higher education (Knowles et al., 2012; Tynjälä, 2013), different types of interventions might be needed in CE compared to higher education (Nawrot & Doucet, 2014; Schröer et al., 2022). Further, other technological and organizational implementation challenges (e.g., special privacy regulations in workplace settings) might occur in CE compared to higher education (Fake & Dabbagh, 2020; Giacumo & Bremen, 2016; Gligorea et al., 2023). Therefore, further research identifying and evaluating interventions for ALEs for CE is needed.

3.5 Research Questions

Based on the research discussed above, we formulated the following research questions:

1. What indicators describing internal and external conditions do learners in CE perceive as relevant to their learning processes and outcomes and should, therefore, be considered by ALEs for CE?

2. Based on these indicators, what interventions for personalizing and supporting learning processes do different stakeholders of ALEs for CE expect?
3. How do different stakeholders of ALEs for CE evaluate these interventions in terms of learners' willingness to use the intervention, perceived learning support, as well as technological and organizational implementation effort?

Study 1 of this paper addresses the first, Study 2 the second, and Study 3 the third research question.

3.6 Study 1

3.6.1 Method

Research Design and Participants

To identify indicators relevant to learning processes and outcomes in CE, we conducted semi-structured, qualitative interviews, which allowed us to collect in-depth information about learners' individual learning experiences in online CE (Cohen et al., 2017). Participants were recruited via social media channels, the network of three German employer associations, and the research team's personal and professional contacts. To participate in the study, participants had to be adults (i.e., at least 18 years old) and have attended at least one CE activity where at least part of the learning activities were delivered online to ensure previous experiences with online learning. As an incentive for participating in the study, participants could take part in a raffle of vouchers with a total value of 200 euros. Following the guidelines proposed by Guest et al. (2006), the recruitment process was continued until saturation was reached, that is, until additional interviews with new participants no longer provided any additional information relevant to our analyses. A total of $N = 37$ participants (23 female, 14 male) were interviewed. Participants were between 22 and 65 years old ($M = 39.92$, $SD = 12.29$) and either (self-) employed across different industries (e.g., information technology, chemical industry, research and education) or looking for work.

Interview Guide

The interview guide consisted of an introduction and a main part. In the introduction part, participants were informed about the purpose of the study, and demographic information (e.g., age, current occupation) was collected. In the main part, participants were first asked to speak about their general learning experiences in online CE ("When you think about your previous experiences with online CE, how did you learn?"). Then, participants were presented with a selection of five to six out of 26 concepts (e.g., emotions, characteristics of the learning materials) related to internal and external conditions of learning. These concepts were derived from Hemmler and Ifenthaler's (2022a) systematic review and have been associated with learning processes and outcomes in empirical studies (for an overview of all concepts used in the interview study, see interview guide in the Online Supplemental Materials). The selection of concepts was made to avoid the duration of the interviews becoming too long. The concepts were selected so that all 26 concepts were evenly distributed across all interviews and so that each participant was confronted with concepts related to both internal and external conditions. For each concept, two guiding questions were asked. First, participants were asked to explain what the respective concept meant to them (e.g., "What do you personally understand by [emotions]?"). The purpose of this question was not to gather information relevant to our analyses but to provide a thought-provoking impulse to help participants answer the subsequent question. Second, participants were asked to explain how the concept influenced their learning processes and outcomes in online CE by providing specific examples (e.g., "When you think about your previous experiences with online CE, to what extent did your [emotions] influence your learning?"). All questions were open-ended and included follow-up questions when clarification was needed. An overview of the interview guide is provided in the Online Supplemental Materials.

Data Collection

The interviews were conducted by the first author of this paper and one trained research assistant. Participants signed the privacy and data protection statement and received the guiding questions of the main part of the interview once the interview date was scheduled to allow them to prepare for the interview. All interviews were voice recorded and lasted between 16 and 59 minutes ($M = 34.18$, $SD = 8.32$). All interviews were conducted in German. Sample quotations presented in this paper (see Section 3.6.2) were translated into English.

Data Analysis

All interviews were transcribed and analyzed using f4transkript (Dresing & Pehl, 2021) and f4analyse (Dresing & Pehl, 2020). To code the interviews, we used deductive and inductive content analysis (Mayring, 2015). Each code corresponded to an indicator (e.g., cognitive strategies) related to internal or external conditions that impacted participants' learning processes or outcomes in online CE. The list of indicators identified in Hemmler and Ifenthaler's (2022a) systematic review was used as a deductive framework. This list of indicators was updated based on the information from the interviews. Indicators not mentioned in the interviews were skipped from the list, and inductive codes for new indicators that emerged from the interviews were added. Similar indicators were clustered into overarching categories (e.g., learning strategies), which, in turn, were grouped into internal and external conditions.

To develop a 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 it was updated accordingly. Once the final version of the coding manual was set, the first author recoded all interviews. A research assistant was trained based on the final version of the coding manual and independently coded a random selection of $n = 8$ interviews. Interrater reliability was good (Krippendorff's $\alpha = .87$). Differences between coders were resolved by discussion. The coding manual can be found in the Online Supplemental Materials.

3.6.2 Results

Internal Conditions

All indicators related to internal conditions identified in the interviews are presented in Table 3-1. These indicators were clustered into the following categories.

Demographics. Participants explained that their marital status and age impacted their motivation for online CE and their time available for learning: "Age also plays a role. I mean, I grew up with technology" (Interview 1). Some participants stated that their parent's level of education served as inspiration for their personal development. Participants' personal level of education influenced the learning strategies they applied as well as the learning content they preferred. For example, one participant explained that she had participated in an online CE activity that did not benefit her because she had already learned the content in previous CE activities: "That was a waste of time and a waste of money […] I already know these principles, as I already have all those licenses […] That should be more individualized" (Interview 30).

Learning Strategies. Participants emphasized the importance of effective SRL strategies (Pintrich et al., 1991; Theobald, 2021). They mentioned that specific cognitive strategies (e.g., rehearsal) helped them acquire learning content: "It is important to repeat the learning content" (Interview 18). Moreover, participants emphasized metacognitive strategies, such as goal setting, planning, and monitoring learning processes, as well as resource management strategies, such as time management and peer learning. Several participants mentioned that bad time management negatively impacted their learning experience: "I am a candidate who has very poor time management when studying. I put it off as long as I can until I panic" (Interview 15). Concerning peer learning, participants showed different preferences. While some participants appreciated interacting and collaborating with peers, others preferred to learn on their own.

Table 3-1

Indicators Related to Internal Conditions

Category	Definition	Indicators
Demographics	Learners' general characteristics representing manifest variables (Wirtz, 2021)	Marital status, age, parent's level of education, personal level of education
Learning strategies	Actions directed at processing information from learning materials or monitoring and regulating learning progress and resources (Pintrich et al., 1993; Zimmerman & Pons, 1986)	Cognitive strategies, metacognitive strategies, resource management strategies
Knowledge, skills, and competences	Cognitive representations and understanding of the learning topic as well as abilities, behaviors, and attitudes necessary to perform a specific task or to be successful in a particular area (Attewell, 1990; Carter, 1985; Le Deist & Winterton, 2005; Winterton et al., 2005)	Prior knowledge, digital literacy, language skills
Personality traits	Characteristics describing interindividual differences in everyday experiences and behaviors that persist over time (McCrae & Costa, 2004; Wirtz, 2021)	Openness to experience, conscientiousness, emotional stability, agreeableness, extraversion
Motivation	Goal-directed attitudes and behaviors driven by learners' desire to perform a specific task well (Brunstein & Heckhausen, 2018); product of individuals' expectancy of how well they will perform a task and the value they attribute to the task (Eccles, 1983; Eccles & Wigfield, 2020, 2023; Wigfield, 1994; Wigfield & Eccles, 2000)	Voluntariness, self-efficacy, task value, learning goals
Psychological needs	Basic psychological prerequisites necessary for healthy and effective functioning, psychological growth, and well-being (Deci & Ryan, 2000; Deci et al., 1996)	Autonomy, competence, relatedness
Emotions	Multifaceted psychological reactions to internal or external circumstances; include cognitive, physiological, affective, and behavioral components (Levenson, 1999; Pekrun & Stephens, 2010; Wirtz, 2021)	Satisfaction, excitement, frustration, boredom
Mental and physical conditions	Learners' mental and physical well-being and states that may influence learners' receptivity for learning (Kokoç et al., 2020; LePine et al., 2004)	Attention, stress, mental and physical health, tiredness
Perception of the CE activity	Learners' subjective evaluations of the CE activity (Hemmler & Ifenthaler, 2022a)	Trust, quality, difficulty
Perceived social influence	Perceived support and pressure from learners' social environments (e.g., coworkers, supervisors, family; Hemmler & Ifenthaler, 2022a)	Social support, social pressure, family commitments
Perception of the job	Learners' work experiences and subjective evaluations of their job (Hemmler & Ifenthaler, 2022a)	Work experience, job satisfaction, learning culture, professional commitments

Note. CE = continuing education.

Knowledge, Skills, and Competences. Participants perceived their learning success to be higher if the learning content matched their individual levels of prior knowledge. They stated that learning was easier if they already knew part of the learning content. However, participants also emphasized the need to learn something new to stay motivated: "If I already know everything, that does not motivate me" (Interview 12). Moreover, participants stated that their digital literacy positively impacted their perceived learning success in online CE: "You also need to be familiar with the tools to make it work" (Interview 2). Participants' language skills determined the language they preferred for the learning content.

Personality Traits. The Big Five personality traits (McCrae & Costa, 2004) were identified to impact perceived learning success and behavior. Participants stated that openness to experience, conscientiousness, and emotional stability were conducive to knowledge acquisition and understanding of learning content in online CE. Moreover, participants mentioned that agreeableness and extraversion impacted the quality of and their desire for social interactions during learning: "I find it very helpful, because I am a very communicative person, when you can exchange ideas with others and build up a relationship with others" (Interview 27).

Motivation. Participants stated that their learning behavior differed depending on whether the participation in the online CE activity was voluntary or imposed by external parties (e.g., employers). Participants were less motivated to learn the learning content thoroughly if the participation was mandatory. According to participants, self-efficacy and task value positively impacted attention: "It was difficult to stay focused on topics that did not interest me" (Interview 4). Moreover, participants were more satisfied with their learning process if the online CE activity helped them achieve their individual learning goals.

Psychological Needs. In accordance with self-determination theory (Deci et al., 1996), participants stated that psychological needs impacted their motivation for CE. Some participants mentioned that their intrinsic motivation decreased if they perceived low levels of autonomy, competence, or relatedness: "If I cannot determine a lot myself, my motivation is impaired" (Interview 13).

Emotions. Participants stated that both positive (satisfaction, excitement) and negative (frustration, boredom) emotions impacted their motivation, attention, and perceived learning success. For example, participants mentioned that they were happy to invest time in CE activities if they were satisfied with and excited about the learning content: "I completed the assignments before the deadline because it was fun" (Interview 13). Further, several participants had difficulties acquiring and understanding new knowledge and content because they were frustrated or bored: "The more monotonous the lesson was, the more difficult it became to follow the lesson" (Interview 23).

Mental and Physical Conditions. According to participants, mental and physical conditions impacted their susceptibility to distractions from learning and their perceived learning success. For example, participants mentioned that stress emerging from family, work, or the online CE activity itself impaired their learning success: “You learn less well under stress” (Interview 26).

Perception of the CE Activity. Participants reported that trust in the online CE activity, perceived quality of the online CE activity, and a positive learning climate were conducive to learning, as these concepts positively impacted their motivation, attention, and satisfaction. Further, participants stated that their motivation was impaired when learning activities were too difficult: “Sometimes, the tasks were so difficult that I had to sit at my desk until 2 a.m. […] I thought learning would be fun, but this was too hard for me” (Interview 27).

Perceived Social Influence. Participants perceived higher levels of motivation and higher learning success if they received social support (e.g., from family, friends). Some participants perceived social pressure to engage in CE activities because individuals from their professional or private environment participated in CE activities: “If I know that a lot of people engage in CE activities […] I like to tag along with them. If they can do it, I can do it, too” (Interview 3). Further, participants mentioned that family commitments sometimes negatively impacted their learning engagement, forcing them to interrupt or postpone learning.

Perception of the Job. If the online CE was work-related, participants stated that their work experience influenced their motivation and the learning content they preferred. The learning content should help learners acquire new knowledge, skills, and competences relevant to their daily work life. Moreover, participants stated that job satisfaction and a positive learning culture within the organization positively impacted their motivation: “My boss always supported me […] And that’s where I often drew my motivation from” (Interview 1). Further, participants stated that professional commitments sometimes negatively impacted their learning engagement, forcing them to interrupt, deprioritize, or postpone learning: “During this time, I had […] a lot of deadlines at work, and I had to postpone my homework a few times” (Interview 18).

External Conditions

All indicators related to external conditions identified in the interviews are presented in Table 3-2. These indicators were clustered into the following categories.

Job Characteristics. Participants mentioned that the number and flexibility of working hours impacted their time available for learning as well as their attention and knowledge acquisition in CE: “If you have a full-time job and you have to learn after a work day […] you cannot absorb much knowledge” (Interview 15). Moreover, depending on their working area, participants were interested in different learning content.

Table 3-2

Indicators Related to External Conditions

Category	Definition	Indicators
Job characteristics	Objective features of learners' job position and work environment (Hemmler & Ifenthaler, 2022a)	Working hours, working area
Characteristics of the CE activity	Objective features of the CE activity (Hemmler & Ifenthaler, 2022a)	Course size, duration, activating teaching methods, feedback, media type, communication tool, flexibility, exams
Characteristics of the CE institution	Objective features of the CE institution (Hemmler & Ifenthaler, 2022a)	Reputation, costs
Spatial and temporal context	Objective features of learners' current location and learning time (Hemmler & Ifenthaler, 2022a)	Technical and material resources, distraction, location, weekday and time, time available for learning

Note. CE = continuing education.

Characteristics of the CE Activity. Participants stated that different characteristics of the CE activity (e.g., course size, duration) impacted their motivation, satisfaction, attention, and perceived learning success: "In many courses, there were 50, 60, or 100 learners. You get lost in the crowd […] I didn't really reflect on the topics" (Interview 28). In general, participants preferred similar characteristics of CE activities. For example, participants generally appreciated activating teaching methods, feedback, and flexibility regarding content, pace, and time: "I like it if you can learn at your own pace" (Interview 7).

Characteristics of the CE Institution. We define a CE institution as the establishment that offers the respective CE activity. A CE institution may be a business organization offering in-company training or other CE providers, such as institutions offering Massive Open Online Courses (MOOCs) or adult education centers. Participants stated that the reputation of the CE institution positively influenced their motivation. Moreover, participants stated that they felt more pressure to successfully complete the CE activity if they had to bear the costs for the CE activity themselves: "Of course, the cost factor should not be underestimated […] I had the feeling that I had to learn as much as possible" (Interview 28).

Spatial and Temporal Context. Technical and material resources (e.g., Internet connection, devices used for learning) had an impact on how well the participants were able to acquire certain learning content: "For this IT training, it would have been better to have a second monitor" (Interview 5). Moreover, several participants mentioned that they were tempted to be distracted during online CE: "There are many ways to get distracted from learning […] You can do something else at the same time" (Interview 33). Participants stated that the location where they were learning (e.g., in the office, at home, on the train) could influence their motivation and attention. Further, participants differed in their preferred weekdays and times for learning. For example, while some participants stated that they learned better in the morning, other participants preferred learning in the evening. Finally, participants perceived their learning success to be higher if both the entire online CE activity and specific learning content within the online CE activity were tailored to their time available for learning: "It is important that you have the necessary time to get involved in the CE activity" (Interview 21).

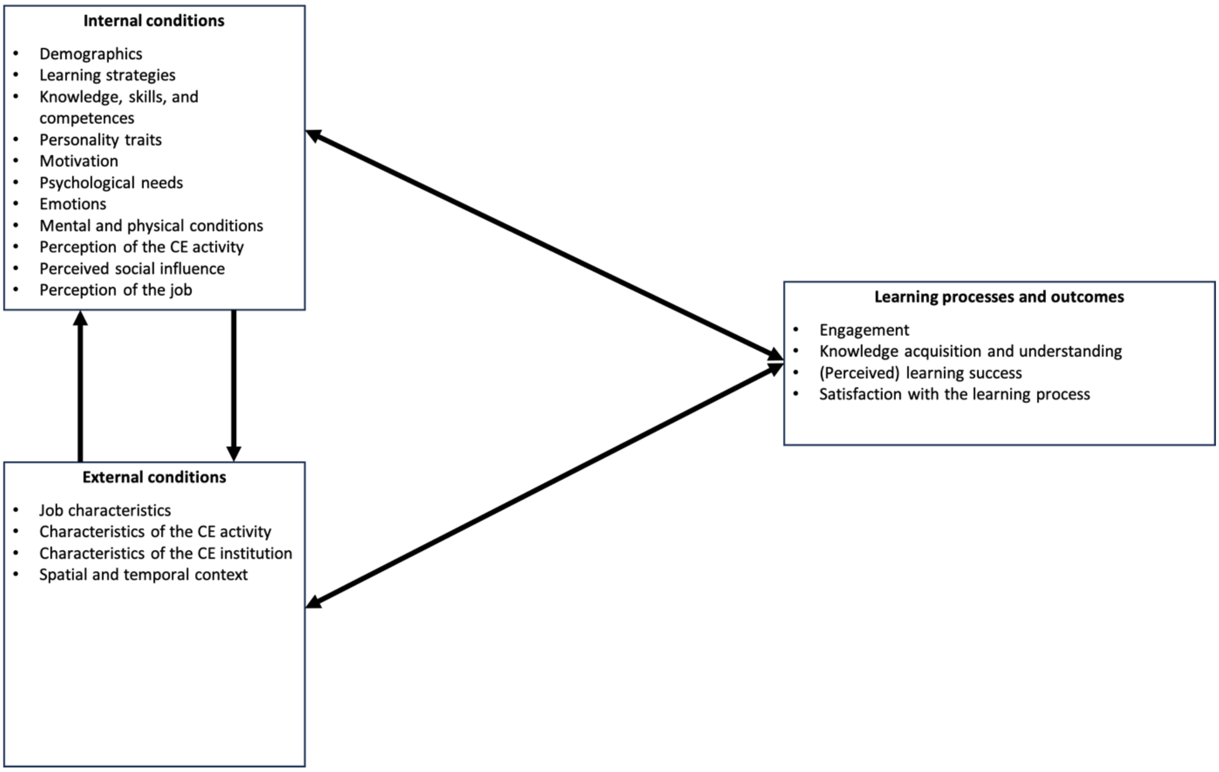
3.6.3 Discussion and Introduction to Study 2

Effective ALEs require reliable indicators that impact learning (Aleven et al., 2017; Plass & Pawar, 2020b). In Study 1, learners' perceptions of their learning experiences in online CE were analyzed to identify indicators relevant to achieving desired learning processes and outcomes in online CE. Several indicators related to learners' internal and external conditions (Winne, 2022; Winne & Hadwin, 1998) were identified. A summarizing overview of the identified categories of indicators related to internal and external conditions, as well as their impacts on learning processes and outcomes, is presented in Figure 3-2. According to participants, indicators related to internal and external conditions are not completely independent but may interact and influence each other (e.g., self-efficacy and task value may influence attention). Internal and external conditions (and their interactions with each other) may impact different learning processes and outcomes, such as engagement and (perceived) learning success. Referring to previous research and learning theories (e.g., Tynjälä, 2013; Winne, 2011, 2022), we suggest that these learning processes and outcomes may have a retroactive effect on learners' conditions. For example, learners' (perceived) learning success may impact their self-efficacy beliefs in the subsequent learning session (Eccles & Wigfield, 2020, 2023; Wigfield & Eccles, 2000). However, these retroactive effects were not the focus of our study.

The indicators identified in our interview study may serve as a basis for designing ALEs for CE. ALEs should address the relationships between conditions and learning processes and outcomes, either strengthening or weakening these relationships to support positive learning processes and outcomes (Li & Wong, 2023; Plass & Pawar, 2020b). Several of the indicators mentioned by participants relate to differences between learners (e.g., age, extraversion) that may serve as a basis for developing task- and step-loop interventions. Further, participants also mentioned indicators that may be similar for all learners (e.g., course size, activating teaching methods) and may serve as a basis for developing design-loop interventions (Aleven et al., 2017). However, it remains unclear how exactly these indicators may be translated into adequate interventions for personalizing and supporting learning processes. Therefore, the purpose of Study 2 was to investigate what interventions different stakeholders of ALEs for CE would expect based on the indicators identified in Study 1.

Figure 3-2

Internal and External Conditions Relevant to Learning Processes and Outcomes in Continuing Education



Note. CE = continuing education.

3.7 Study 2

3.7.1 Method

Research Design and Participants

To identify interventions for ALEs for CE, we conducted semi-structured, qualitative focus group interviews in which participants were asked to generate ideas for interventions based on the indicators identified in Study 1. We suggested that generating ideas for ALEs would be a rather unfamiliar task for most of the participants. Therefore, we decided to conduct focus groups with a group size of three to four participants each, so that participants could build on the others' ideas and arguments (Johansson et al., 2018). The selected group size has been shown to allow for rich group discussion while enabling effective online communication (Johansson et al., 2018; Lobe, 2017; Schneider et al., 2016).

In total, we conducted six focus group interviews. Three focus group interviews were conducted with potential learners in CE (i.e., adults with different educational backgrounds and occupations). An additional three focus group interviews were conducted with CE specialists and educational technology specialists. We decided to divide the groups into learner and specialist focus groups and not to conduct mixed groups to avoid dominance effects (Nyumba et al., 2018) of the specialists.

Participants were recruited using the same recruitment procedures as in Study 1 (i.e., the network of three German employer associations, social media, the research team's personal and professional contacts). To participate in the learner focus groups, participants had to be adults (i.e., at least 18 years old). To participate in the specialist focus groups, participants had to be adults and currently working either in the field of CE or in the field of educational technology. A total number of $N = 19$ participants took part in the study. The sample consisted of $n = 10$ potential learners (8 female, 2 male; age: 27–35, $M = 28.70$, $SD = 2.50$) working in different professions (e.g., media designer, midwife) and $n = 9$ specialists (e.g., training manager, research associate in educational technology, 7 female, 2 male; age[1]: 26–41, $M = 33.25$, $SD = 10.69$). Participants received a 20-euro voucher for participating in the focus group interview and a subsequent online survey (Study 3).

Interview Guide

The focus group interviews consisted of three parts. The content and guiding questions of all three parts were presented to the participants on PowerPoint slides in addition to communicating them verbally. In the first part, participants were informed about the purpose of the study and the detailed procedure of the focus group interview. In the second part, participants were given an introduction to the functionality and benefits of ALEs for CE. In the third part, participants were presented with a selection of five out of the 15 categories of indicators identified in Study 1 (see Table 3-1 and Table 3-2). The selection of categories was made to avoid the duration of the interviews becoming too long. The categories were divided up so that each category was dealt with in both a learner and a specialist focus group. For each category, participants were presented with the findings of Study 1, that is, the indicators of the category and their impacts on learning processes and outcomes in online CE. Then, participants were asked to generate interventions for ALEs based on these indicators (e.g., "How should

[1] One participant did not provide detailed information on age.

ALEs adapt to indicators of learners' [emotions]?"). For each category, participants were first given 3 minutes of individual brainstorming. Participants could record their individual ideas on an online notepad to which the other participants did not have access. Then, participants were asked to discuss their ideas in the group. The moderator (the first author of this paper) of the focus group made sure that the speaking time was balanced between participants and asked follow-up questions when clarification was needed. An overview of the interview guide is presented in the Online Supplemental Materials.

Data Collection

All focus group interviews were conducted via videoconference. Participants could register for the study via a Qualtrics survey. In this survey, participants' agreement with the privacy and data protection statement, as well as demographic information (e.g., age, current occupation), was collected. Moreover, participants had to indicate whether they self-identified as CE specialists or educational technology specialists (i.e., whether they were currently working in the field of CE or educational technology). Based on this information, participants were assigned either to a learner or a specialist focus group. All group discussions (part three of the interview guide) were video recorded and lasted between 37 and 48 minutes ($M = 43.73$, $SD = 3.69$). All focus group interviews were conducted in German. Sample quotations from the focus group interviews presented in this paper (see Table 3-3) were translated into English.

Data Analysis

All group discussions were transcribed using f4transkript (Dresing & Pehl, 2021). The transcripts and the entries in the online notepads from the individual brainstorming phases were analyzed using f4analyse (Dresing & Pehl, 2020). To code the materials, we first deployed inductive content analysis (Mayring, 2015). Each code corresponded to an intervention for personalizing or supporting learning processes in CE using ALEs. The first author of this paper coded all focus group interviews to develop a coding manual, which was then discussed and updated by the research team. Once the coding manual was updated, the first author recoded all interviews. Moreover, a trained research assistant independently coded all interviews. Interrater reliability was good (Krippendorff's $\alpha = .82$). Differences between coders were resolved by discussion. Then, deductive content analysis was deployed to classify the interventions. For each intervention, the same two coders independently assigned the indicators from Study 1 that were addressed by the intervention (Krippendorff's $\alpha = .93$) and determined whether the intervention was a task-loop, step-loop, or design-loop intervention (Krippendorff's $\alpha = .70$) according to Aleven et al. (2017). Again, differences between coders were resolved by discussion. The coding manual can be found in the Online Supplemental Materials.

3.7.2 Results

All interventions identified in the focus group interviews, as well as their assigned indicators and adaptivity type, are presented in Table 3-3. A total number of 37 interventions were identified. Participants mentioned several task-loop and step-loop interventions as well as one design-loop intervention. The task-loop interventions mainly focused on the adaptation of the learning content (e.g., the difficulty level, the thematic focus, the learning duration) as well as the recommendation of learning resources based on specific indicators such as time available for learning or working area. The step-loop interventions mainly focused on the presentation of additional assistance (e.g., adaptive presentation of assistance with the digital learning system) as well as on features that trigger specific SRL strategies (e.g., prompts for specific learning strategies) and help learners manage their time resources (e.g., adaptive learning calendar), monitor their individual learning progress (e.g., dashboards), as well as regulate internal conditions such as motivation or emotions (e.g., emphasis of personal relevance). The design-loop intervention (adaptive group size) focused on iterative adaptations of the group size for a specific learning topic or task. Although the interventions mentioned by participants addressed all indicator categories from Study 1, for some specific indicators (e.g., parent's level of education, reputation), no intervention was identified.

Table 3-3

Interventions for Adaptive Learning Environments for Continuing Education

Intervention	Description	Sample quotation	Related indicators from Study 1	Adaptivity type	Focus group
Adaptation of the complexity	The system continuously adjusts the complexity of the learning content (e.g., regarding difficulty level, topic, and duration) to the learner's current level of attention	"If you are already burdened, it would also make sense to make the learning content easier, that is, to learn less complex content on that day" (Group 1, Person 3)	• Attention	Task-loop	L
Adaptation of the frequency of pop-ups and prompts	The system continuously adjusts the frequency of pop-ups and prompts to the learner's current level of stress (fewer pop-ups and prompts with high levels of stress)	"Especially when you are stressed, my idea would have been to include as few pop-ups as possible" (Group 5, Person 2)	• Stress	Step-loop	S
Adaptation of the general difficulty level and thematic focus	The system adapts the difficulty level or thematic focus of the CE activity to the learner's prior experiences (e.g., level of education, work experience) or knowledge	"Examination of the prior knowledge, the level of education […] Based on that, one learner is given the following tasks to learn, the other the other tasks" (Group 3, Person 1)	• Personal level of education • Prior knowledge • Work experience	Task-loop	L & S

Intervention	Description	Sample quotation	Related indicators from Study 1	Adaptivity type	Focus group
Adaptation of the language or language assistance	The system adapts the learning content to the learner's language skills (e.g., automatic translation into the learner's native language, additional explanations for technical terms)	"If the artificial intelligence notices that someone's language skills are not good, it could suggest a brief explanation for new or technical terms" (Group 4, Person 2)	• Language skills	Step-loop	L & S
Adaptation of the learning duration	If the learner is highly motivated, excited, and perceives no stress, learning resources with a longer duration are provided	"You may ask at the beginning of a learning unit what the mood is like. And if there is excitement, you offer a larger learning unit" (Group 3, Person 1)	• Self-efficacy • Task-value • Excitement • Stress	Task-loop	L & S
Adaptation of the learning format	If the learner appreciates peer learning and social interactions, the CE activity is offered in a synchronous format (vs. an asynchronous format for learners with no preference for peer learning and social interactions)	"Introverted people would probably feel uncomfortable if they had to learn synchronously in a big group of learners" (Group 3, Person 1)	• Resource management strategies • Extraversion • Relatedness	Task-loop	L & S
Adaptation of the motivational support	The system provides stronger motivational support (e.g., gamification, reminders) if learners do not have to bear the costs of the CE activity themselves or if the costs are low	"If it doesn't cost anything, you could try to keep people motivated with gamification challenges" (Group 5, Person 2)	• Costs	Step-loop	L & S
Adaptation to device and location	The system adapts the learning content to the learner's device used for learning and current location (e.g., no long texts on a small screen, video with headphones vs. text depending on noise level at the location)	"Small text is a bit awkward when you learn with your cell phone. Then, a video may be offered" (Group 5, Person 1)	• Technical and material resources • Location	Task-loop/step-loop	L & S
Adaptation to mental and physical handicaps	The system respects mental and physical handicaps (e.g., a read-aloud function or audio content for visually impaired people)	"There may be people that are visually impaired […] There should be a read-aloud function or something like that for these people" (Group 2, Person 1)	• Mental and physical health	Step-loop	L
Adaptation to the quality of the Internet connection	The system adapts the learning content to the quality of the Internet connection (e.g., offline materials or no large videos with a poor Internet connection)	"And that the system can also detect if you have a poor Internet connection, so that the content is either offered offline or perhaps no large videos are displayed" (Group 4, Person 1)	• Technical and material resources	Task-loop/step-loop	L & S
Adaptive breaks	The system suggests the learner take a break if the learner is frustrated, inattentive, stressed, or tired	"Maybe, the system can also learn when a person needs a break and introduce adaptive breaks" (Group 5, Person 1)	• Frustration • Attention • Stress • Tiredness	Step-loop	L & S
Adaptive group size	The system automatically determines the ideal size of a learning group (e.g., group size for group tasks) for a specific topic or task and adapts the size in the next iteration	"Detecting the learning progress for different group sizes and topics and adapting the group size accordingly" (Group 6, Person 1)	• Course size	Design-loop	S

Intervention	Description	Sample quotation	Related indicators from Study 1	Adaptivity type	Focus group
Adaptive learning calendar	The system provides a calendar that enables learners to block time for learning, allows synchronization with the professional and private calendar, and sends warnings in the event of overlapping appointments	"That you can connect the learning environment with your calendar program, and when you open a learning activity, a warning message appears if the duration of the learning activity overlaps with your next appointment" (Group 4, Person 3)	• Family commitments • Professional commitments • Time available for learning	Step-loop	S
Adaptive learning points and awards	For learners with a strong need for competence, the system offers the opportunity to collect learning points or awards	"You might get some kind of virtual reward, some kind of badges or stickers or points that you can collect. And if your need for competence is low, then you might get fewer rewards or none at all. And if you have a high need for competence, you might get points more quickly" (Group 5, Person 2)	• Competence	Step-loop	L & S
Adaptive presentation of assistance with the digital learning system	If the learner is lacking in digital literacy, the system offers additional support with the digital learning environment	"Concerning digital literacy, maybe an introduction to the learning system might be helpful. This could also be adaptive, depending on whether the learner needs it or not" (Group 4, Person 3)	• Digital literacy	Step-loop	L & S
Adaptive presentation of further assistance	If the learner is frustrated or perceives the learning content as too difficult, the system provides additional explanations and assistance	"Concerning perceived difficulty […] additional explanations or help may appear" (Group 4, Person 3)	• Frustration • Difficulty	Step-loop	L & S
Coaching-chatbot	The system includes a chatbot that provides personalized coaching on personal development and personal learning goals, and provides suggestions on how to reconcile learning with other commitments (e.g., family or professional commitments)	"If there was a chatbot integrated into the learning environment, you could use it when you are faced with challenges due to family or career reasons" (Group 4, Person 3)	• Learning goals • Family commitments • Professional commitments	Step-loop	S
Context adaptation	The system adapts the context of the learning content to the learner's job tasks (e.g., demonstration through examples from everyday work life)	"That the system is tailored to the learner's to-dos, with practical examples from everyday work life" (Group 5, Person 3)	• Working area	Task-loop	L & S
Continuous adjustment of the difficulty level	The system continuously adjusts the difficulty level to the learner's individual learning performance and perceived difficulty	"A prompt where you can indicate […] whether you are overchallenged or underchallenged. And then, the system may adapt to that" (Group 5, Person 3)	• Difficulty	Task-loop	L & S
Dashboards	Dashboards that visualize the learner's individual goal progress and provide comparisons with peers	"That you can see on a dashboard what you have achieved already" (Group 6, Person 3)	• Learning goals	Step-loop	L & S

Intervention	Description	Sample quotation	Related indicators from Study 1	Adaptivity type	Focus group
Detection of satisfactory learning conditions	The system recognizes under which conditions (e.g., topic, learning pace, user interface) the learner is satisfied and maintains these conditions	"If satisfied, I would simply maintain the learning content, the pace, the quantity" (Group 3, Person 1)	• Satisfaction	Task-loop/step-loop	L & S
Emphasis of personal relevance	The system provides pop-ups or short hints that highlight the personal relevance of the learning content for the learner's everyday (work) life	"A short pop-up that emphasizes the personal relevance of the topics and how they help you in your professional or private life" (Group 4, Person 1)	• Task value	Step-loop	L & S
Individual countdowns	The system displays an individual countdown for (self-set) deadlines and exams	"That a countdown is displayed on the interface" (Group 3, Person 1)	• Metacognitive strategies • Resource management strategies • Exams • Time available for learning	Step-loop	L
Individual reminders	Reminders where learners can set whether, when, and how they would like to be reminded to learn (e.g., via e-mail, push-notifications)	"That you get reminders. And you can set when you want to receive them" (Group 2, Person 2)	• Metacognitive strategies • Resource management strategies • Weekday and time • Time available for learning	Step-loop	L & S
Recommendation of activation/ relaxation exercises	The system provides recommendations of activation and/or relaxation exercises based on the learner's current level of attention, stress, or tiredness	"And maybe, the system can measure a learner's tiredness […] and suggest exercises to energize the circulation" (Group 5, Person 2)	• Attention • Stress • Tiredness	Step-loop	L & S
Recommendation of goal-oriented learning resources	The system provides recommendations of CE activities or learning content that help learners achieve their personal goals	"Where do I want to go? What is my goal? This should also be taken into consideration" (Group 2, Person 2)	• Learning goals	Task-loop	L & S
Recommendation of learning partners	Recommendation of suitable learning partners if the learner appreciates peer learning and social interactions	"Concerning agreeableness: If you are agreeable, you can do group work. If not, you should maybe learn alone" (Group 1, Person 3)	• Resource management strategies • Agreeableness • Extraversion • Relatedness	Step-loop	L & S
Recommendation of learning resources based on interests	The system provides recommendations of CE activities or learning content that match the learner's personal interests	"Perhaps, you could also track how long a learner watches certain learning content, as this might be an indicator that the personal interest for this learning content or topic is higher" (Group 4, Person 3)	• Task value	Task-loop	S
Recommendation of learning resources relevant to the working area	The system provides recommendations of CE activities or learning content that are specifically useful in the learner's working area	"Recommendation of topics that are a perfect fit for my working area" (Group 6, Person 1)	• Working area	Task-loop	S

Intervention	Description	Sample quotation	Related indicators from Study 1	Adaptivity type	Focus group
Recommendation of learning resources that colleagues have completed	The system provides recommendations of CE activities or learning content that the learner's colleagues have already completed	"Perhaps a bit of peer pressure by recommending CE activities that colleagues have completed" (Group 5, Person 3)	• Social pressure • Working area	Task-loop	S
Recommendation of learning times	The system recognizes when (weekday and time) a learner learns most effectively and recommends learning times accordingly	"A program that could somehow measure performance over the course of a day. So that it can reflect the most effective learning times back to the individual learner" (Group 1, Person 2)	• Resource management strategies • Weekday and time	Step-loop	L & S
Recommendation of learning resources based on available time	The system provides recommendations of CE activities or learning content based on the amount of time the learner can invest in learning	"I would also like it if you could indicate how much time you have available […] And then, the next learning unit is adapted to the time I have available" (Group 1, Person 3)	• Time available for learning	Task-loop	L & S
Personalized feedback	Personalized feedback on learning strategies and learning goal progress	"That you get individualized feedback […] based on your learning progress" (Group 6, Person 1)	• Cognitive strategies • Metacognitive strategies • Resource management strategies • Leaning goals	Step-loop	L & S
Presentation of activating learning resources	The system changes learning activities (e.g., change of topic, group work) if the learner is bored	"And if you get bored, the system may change the learning method" (Group 3, Person 1)	• Boredom	Task-loop	L & S
Presentation of alternative learning content	The system recommends alternative learning content if a learner is frustrated	"Or the system may change the topic and suggest another one, with which you might want to continue learning. Then, you can come back to the previous topic another day" (Group 3, Person 1)	• Frustration	Task-loop	L
Prompts for specific learning strategies	Based on individual learning behavior, the system recognizes the learning strategy (e.g., rehearsal, self-monitoring, peer learning) that the learner should apply and sends prompts that trigger this strategy	"That the system tells you if you should apply the strategy rehearsal" (Group 6, Person 1)	• Cognitive strategies • Metacognitive strategies • Resource management strategies	Step-loop	L & S
Warning in case of distraction	The system detects potential distractions (e.g., Internet pages opened in parallel, noises in the background) and reminds learners to concentrate on learning	"If the system could recognize distraction. For example, whether there are noises in the background or whether learners have opened other websites in parallel. And then, the system reminds them that they should concentrate on learning" (Group 1, Person 2)	• Distraction	Step-loop	L

Note. Groups 1–3: learner focus groups. Groups 4–6: specialist focus groups. CE = continuing education; L = learners (indicates that the intervention was mentioned in at least one learner focus group); S = specialists (indicates that the intervention was mentioned in at least one specialist focus group).

3.7.3 Discussion and Introduction to Study 3

Interventions for ALEs may address different indicators and be based on similarities or differences between learners (Aleven et al., 2017; Davis et al., 2016; Rasch & Middelbeck, 2022). In Study 2, we conducted focus group interviews to identify interventions that learners in CE, CE specialists, and educational technology specialists expect from ALEs. These interventions were classified based on the indicators they address as well as based on the adaptivity type according to Aleven et al. (2017). The list of interventions identified in Study 2 may serve as a useful basis for designing ALEs for CE. However, it remains unclear which of these interventions are best suited for the context of CE. For example, different interventions may be perceived differently in terms of learners' willingness to use the intervention and perceived learning support (Schumacher & Ifenthaler, 2018; Schumacher et al., 2019). Further, some interventions may be less feasible or require more implementation effort than others (Schumacher et al., 2019). Therefore, the purpose of Study 3 was to evaluate the list of interventions in terms of learners' willingness to use the intervention, perceived learning support, as well as technological and organizational implementation effort.

3.8 Study 3

3.8.1 Method

Research Design and Participants

To provide quantitative evaluations of the interventions from Study 2, Study 3 consisted of a quantitative online survey. All participants from Study 2 were invited to participate in Study 3. Eighteen participants from Study 2 agreed to participate in the online survey. An additional 54 participants were recruited using the same recruitment procedures as in Study 1 and Study 2. Thus, a total number of $N = 72$ participants took part in Study 3. To participate in the study, participants had to be adults (i.e., at least 18 years old). The sample consisted of $n = 54$ potential learners (74% working adults, 15% students, 13% other; 44 female, 10 male; age: 20–79, $M = 37.72$, $SD = 16.54$) and $n = 18$ specialists working in the field of CE or educational technology (e.g., training manager, coach, research associate; 10 female, 8 male; age: 18–58, $M = 34.11$, $SD = 10.43$). As mentioned in Section 3.7.1, participants who had already participated in Study 2 received a 20-euro voucher for participating in both studies. No compensation was provided to participants who only participated in Study 3.

Data Collection and Instruments

Data collection took place via Qualtrics. The survey consisted of three parts, whereby the first and second parts were omitted for participants who had already taken part in Study 2, as these parts had been carried out as part of Study 2. In the first part, participants agreed to the privacy and data protection statement, and demographic information (e.g., age, gender, current occupation) was collected. Moreover, participants had to indicate whether they self-identified themselves as CE or educational technology specialists (i.e., whether they were currently working in the field of CE or educational technology). In the second part, participants were given a short introduction to the functionality and benefits of ALEs for CE. In the third part, participants were presented with the interventions from Study 2. To ensure that the survey could be completed in a reasonable amount of time, each participant was presented with a random selection of 17 interventions. Filtering questions were used to present different questions depending on whether the participants were identified as CE or educational technology specialists. If participants were not identified as CE or educational technology specialists, they were considered as potential learners and were asked to evaluate the 17 interventions in terms of willingness to use the intervention and perceived learning support. The CE and educational technology specialists were asked to evaluate the interventions in terms of technological and organizational implementation effort. The four evaluation variables were derived from Schumacher et al.'s (2019) study and were each assessed with one item on a 7-point Likert scale (see Table 3-4 for more details on items and scales).

Table 3-4

Information on Items From Study 3

Variable	Item	Scale
Willingness to use	"To what extent would you like to use this intervention as a learner in online CE?"	1 = not at all, 7 = extremely
Perceived learning support	"To what extent do you think this intervention could support your learning processes in online CE?"	1 = not at all, 7 = extremely
Technological implementation effort	"How high do you estimate the technological effort (e.g., concerning the development of the data collection structure and the integration into a corresponding learning environment) to implement this intervention in online CE?"	1 = very low, 7 = very high
Organizational implementation effort	"How high do you estimate the organizational effort (e.g., with regard to data protection regulations, the curation of learning materials, and the training of CE staff) to implement this intervention in online CE?"	1 = very low, 7 = very high

Note. CE = continuing education. The survey was conducted in German. The items were translated into English to present them in this paper.

Data Analysis

Data analysis was conducted in R (version 4.3.0). For each intervention, we calculated the mean of willingness to use and perceived learning support across all potential learners, as well as the mean of technological and organizational implementation effort across all specialists who evaluated the intervention. Moreover, for each intervention, a total learner score and a total specialist score were created by aggregating all evaluations on the two respective items (i.e., willingness to use and perceived learning support for the total learner score, technological and organizational implementation effort for the total specialist score). A prioritization of the interventions was created by assorting the total learner and the total specialist scores. Accordingly, the interventions with the highest willingness to use and perceived learning support, as well as those with the lowest technological and organizational implementation effort, were considered to have the highest priority.

3.8.2 Results

Means and standard deviations for the top 10 prioritized interventions by potential learners are presented in Table 3-5. Means and standard deviations for the top 10 prioritized interventions by the specialists are presented in Table 3-6. Evaluations of all other interventions can be found in Appendix A. The most highly prioritized interventions by the potential learners were adaptation of the general difficulty level and thematic focus, adaptive presentation of further assistance, and continuous adjustment of the difficulty level. According to the specialists, the interventions with the lowest implementation effort were individual countdowns, individual reminders, and dashboards.

Table 3-5

Potential Learners' Evaluation of Interventions (Top 10)

Prioritization score	Intervention	Total	Willingness to use	Perceived learning support
1	Adaptation of the general difficulty level and thematic focus	*M* = 6.48, *SD* = 1.02	*M* = 6.43, *SD* = 1.03	*M* = 6.52, *SD* = 1.03
2	Adaptive presentation of further assistance	*M* = 6.32, *SD* = 0.89	*M* = 6.37, *SD* = 0.96	*M* = 6.26, *SD* = 0.87
3	Continuous adjustment of the difficulty level	*M* = 6.18, *SD* = 1.03	*M* = 6.12, *SD* = 1.17	*M* = 6.24, *SD* = 0.97
4	Context adaptation	*M* = 6.17, *SD* = 1.28	*M* = 6.17, *SD* = 1.29	*M* = 6.17, *SD* = 1.38
5	Prompts for specific learning strategies	*M* = 6.16, *SD* = 0.75	*M* = 6.11, *SD* = 0.99	*M* = 6.21, *SD* = 0.63
6	Adaptation of the complexity	*M* = 5.95, *SD* = 1.09	*M* = 5.95, *SD* = 1.16	*M* = 5.95, *SD* = 1.20
7	Recommendation of learning times	*M* = 5.74, *SD* = 1.12	*M* = 5.53, *SD* = 1.28	*M* = 5.94, *SD* = 1.09
8	Adaptation of the learning format	*M* = 5.71, *SD* = 1.53	*M* = 5.71, *SD* = 1.61	*M* = 5.71, *SD* = 1.53
9	Recommendation of goal-oriented learning resources	*M* = 5.69, *SD* = 1.21	*M* = 5.67, *SD* = 1.20	*M* = 5.71, *SD* = 1.27
10	Recommendation of learning resources based on available time	*M* = 5.59, *SD* = 1.41	*M* = 5.75, *SD* = 1.36	*M* = 5.44, *SD* = 1.58

Note. Evaluation on a 7-point Likert scale: 1 = very low willingness to use/perceived learning support, 7 = very high willingness to use/perceived learning support.

Table 3-6

Continuing Education/Educational Technology Specialists' Evaluation of Interventions (Top 10)

Prioritization score	Intervention	Total	Willingness to use	Perceived learning support
1	Individual countdowns	*M* = 1.64, *SD* = 0.75	*M* = 1.86, *SD* = 1.07	*M* = 1.43, *SD* = 0.53
1	Individual reminders	*M* = 1.64, *SD* = 0.48	*M* = 1.29, *SD* = 0.49	*M* = 2.00, *SD* = 0.82
3	Dashboards	*M* = 2.70, *SD* = 1.35	*M* = 2.60, *SD* = 1.14	*M* = 2.80, *SD* = 1.64
4	Adaptive learning points and awards	*M* = 2.75, *SD* = 1.07	*M* = 2.50, *SD* = 1.31	*M* = 3.00, *SD* = 1.07
5	Recommendation of learning resources that colleagues have completed	*M* = 2.79, *SD* = 1.11	*M* = 2.43, *SD* = 1.27	*M* = 3.14, *SD* = 1.46
6	Recommendation of learning resources based on available time	*M* = 2.85, *SD* = 1.51	*M* = 2.55, *SD* = 1.52	*M* = 3.15, *SD* = 1.78
7	Adaptation to the quality of the Internet connection	*M* = 2.92, *SD* = 0.86	*M* = 3.17, *SD* = 1.17	*M* = 2.67, *SD* = 1.03
8	Recommendation of learning resources relevant to the working area	*M* = 3.29, *SD* = 0.95	*M* = 2.71, *SD* = 1.11	*M* = 3.86, *SD* = 1.21
9	Adaptive learning calendar	*M* = 3.42, *SD* = 1.88	*M* = 3.50, *SD* = 2.17	*M* = 3.33, *SD* = 2.07
10	Adaptation of the language or language assistance	*M* = 3.43, *SD* = 0.98	*M* = 3.14, *SD* = 1.35	*M* = 3.71, *SD* = 0.95

Note. Evaluation on a 7-point Likert scale: 1 = very low implementation effort, 7 = very high implementation effort

Figure 3-3

Framework of Indicators and Interventions for Adaptive Learning Environments for Continuing Education

Indicator (Study 1)	Intervention (Study 2): Task-loop	Evaluation (Study 3) L	Evaluation (Study 3) S	Step-loop	Evaluation (Study 3) L	Evaluation (Study 3) S	Design-loop	Evaluation (Study 3) L	Evaluation (Study 3) S
Level of education	Adaptation of the general difficulty level and thematic focus	6.48	4.25						
Cognitive strategies				Prompts for specific learning strategies	6.16	4.92			
				Personalized feedback	5.18	4.50			
Metacognitive strategies				Individual countdowns	5.33	1.64			
				Individual reminders	4.33	1.64			
				Prompts for specific learning strategies	6.16	4.92			
				Personalized feedback	5.18	4.50			
Resource management strategies	Adaptation of the learning format	5.71	5.17	Individual countdowns	5.33	1.64			
				Individual reminders	4.33	1.64			
				Recommendation of learning times	5.74	4.20			
				Prompts for specific learning strategies	6.16	4.92			
				Personalized feedback	5.18	4.50			
				Recommendation of learning partners	5.05	4.64			
Prior knowledge	Adaptation of the general difficulty level and thematic focus	6.48	4.25						
Digital literacy				Adaptive presentation of assistance with the digital learning system	5.24	4.00			
Language skills				Adaptation of the language or language assistance	5.42	3.43			
Agreeableness				Recommendation of learning partners	5.05	4.64			
Extraversion	Adaptation of the learning format	5.71	5.17	Recommendation of learning partners	5.05	4.64			
Self-efficacy	Adaptation of the learning duration	5.18	5.00						
Task value	Adaptation of the learning duration	5.18	5.00	Emphasis of personal relevance	4.98	4.64			
	Recommendation of learning resources based on interests	5.31	5.33						
Learning goals	Recommendation of goal-oriented learning resources	5.69	3.67	Dashboards	4.83	2.70			
				Personalized feedback	5.18	4.50			
				Coaching-chatbot	4.71	5.50			
Competence				Adaptive learning points and awards	4.23	2.75			
Relatedness	Adaptation of the learning format	5.71	5.17	Recommendation of learning partners	5.05	4.64			
Satisfaction	Detection of satisfactory learning conditions	5.39	4.83	Detection of satisfactory learning conditions	5.39	4.83			
Frustration	Presentation of alternative learning content	5.16	5.43	Adaptive presentation of further assistance	6.32	3.57			
				Adaptive breaks	5.05	4.00			
Boredom	Presentation of activating learning resources	5.41	4.57						
Attention	Adaptation of the complexity	5.95	4.64	Adaptive breaks	5.05	4.00			
				Recommendation of activation/relaxation exercises	4.34	4.21			
Stress	Adaptation of the learning duration	5.18	5.00	Adaptive breaks	5.05	4.00			
				Adaptation of the frequency of pop-ups and prompts	4.59	4.25			
				Recommendation of activation/relaxation exercises	4.34	4.21			
Mental and physical health				Adaptation to mental and physical handicaps	5.44	4.94			
Tiredness				Adaptive breaks	5.05	4.00			
				Recommendation of activation/relaxation exercises	4.34	4.21			
Difficulty	Continuous adjustment of the difficulty level	6.18	4.58	Adaptive presentation of further assistance	6.32	3.57			
Social pressure	Recommendation of learning resources that colleagues have completed	4.53	2.79						
Family commitments				Coaching-chatbot	4.71	5.50			
				Adaptive learning calendar	3.43	3.42			
Work experience	Adaptation of the general difficulty level and thematic focus	6.48	4.25						
Professional commitments				Coaching-chatbot	4.71	5.50			
				Adaptive learning calendar	3.43	3.42			
Working area	Recommendation of learning resources relevant to the working area	5.35	3.29						
	Recommendation of learning resources that colleagues have completed	4.53	2.79						
	Context adaptation	6.17	4.71						
Course size							Adaptive group size	4.81	3.86
Exams				Individual countdowns	5.33	1.64			
Costs				Adaptation of the motivational support	4.75	3.75			
Technical and material resources	Adaptation to the quality of the Internet connection	5.40	2.92	Adaptation to the quality of the Internet connection	5.40	2.92			
	Adaptation to device and location	5.13	4.09	Adaptation to device and location	5.13	4.09			
Distraction				Warnings in case of distraction	4.40	5.17			
Weekday and time				Individual reminders	4.33	1.64			
				Recommendation of learning times	5.74	4.20			
Time available for learning	Recommendation of learning resources based on available time	5.59	2.85	Individual countdowns	5.33	1.64			
				Individual reminders	4.33	1.64			
				Adaptive learning calendar	3.43	3.42			

Evaluation (Study 3)

L = total learner score:

1 = very low willingness to use/perceived learning support,
7 = very high willingness to use/perceived learning support

6.00 <= L <= 7.00
5.00 <= L < 6.00
4.00 <= L < 5.00
3.00 <= L < 4.00
2.00 <= L < 3.00
1.00 <= L < 2.00

S = total specialist score:

1 = very low technological/organizational implementation effort,
7 = very high technological/organizational implementation effort

6.00 <= S <= 7.00
5.00 <= S < 6.00
4.00 <= S < 5.00
3.00 <= S < 4.00
2.00 <= S < 3.00
1.00 <= S < 2.00

3.9 General Discussion

ALEs provide great potential for personalizing and supporting learning processes in CE (Hemmler & Ifenthaler, 2022b; Plass & Pawar, 2020b). However, valid frameworks for designing ALEs for CE have been missing so far (Bernacki et al., 2021; Li & Wong, 2023; Xie et al., 2019). Therefore, in this paper, different stakeholders' perspectives on ALEs for CE were analyzed using a mixed-methods approach. Several indicators (e.g., learning goals) and corresponding interventions (e.g., recommendation of goal-oriented learning resources) for ALEs for CE were identified and evaluated in terms of learners' willingness to use the intervention, perceived learning support, and implementation effort. Figure 3-3 summarizes the findings of all three studies and integrates them into a framework of indicators and interventions for ALEs for CE. The indicators on the left side of the framework are based on the findings from Study 1, while the interventions and their classification based on indicators and adaptivity type (task-loop, step-loop, design-loop; Aleven et al., 2017) stem from Study 2. Study 3 contributes to the framework by prioritizing the interventions based on learners' and specialists' evaluations.

3.9.1 Interpretation of Results and Theoretical Implications

The indicators identified in Study 1 refer to internal and external conditions (Winne, 2022; Winne & Hadwin, 1998) affecting learning processes or outcomes in online CE. Researchers have suggested that only indicators relevant to achieving desired learning processes and outcomes should be considered for ALEs, as these indicators may serve as a reliable basis for designing interventions (Aleven et al., 2017; Plass & Pawar, 2020b). Thus, our study adds to previous research by providing an empirical list of potential indicators for ALEs for CE.

Existing ALEs for CE have focused on trace data indicators (e.g., Davis et al., 2016; Pérez-Álvarez et al., 2020), prior knowledge (e.g., Rasch & Middelbeck, 2022; Xue-jun et al., 2021), learning goals (e.g., Tavakoli et al., 2022), or learning styles (e.g., Chaipidech et al., 2022; Xue-jun et al., 2021). The findings of Study 1 show that many additional indicators may be suitable for ALEs for CE. While prior knowledge and learning goals have also been mentioned in Study 1, the study cannot provide empirical support for trace data indicators and learning styles. Study 1 aimed at identifying theoretical constructs relevant to ALEs and not trace data indicators. Nevertheless, when embedded in learning theories, trace data may have great potential for the design of ALEs, as they may provide insights into individual learning behavior (Araka et al., 2020; Gašević et al., 2016; Winne, 2011). Although learning styles have been commonly discussed in the context of ALEs (Katsaris & Vidakis, 2021; Xue-jun et al., 2021), the existence and validity of different learning styles, as well as their relevance for learning processes and outcomes, have been strongly criticized in educational psychology research (Coffield et al., 2004; Kirschner, 2017). Therefore, researchers have argued that including learning styles in ALEs is not beneficial (Bernacki et al., 2021; Plass & Pawar, 2020b). Our study supports this argumentation by showing that other indicators seem to be more relevant to the context of CE than learning styles.

Several indicators identified in Study 1 (e.g., resource management strategies, time available for learning) relate to learners' use of SRL strategies and personal time resources. This is consistent with previous research that identified inefficient SRL strategies, such as inefficient time management, and lack of time as main barriers to CE (Eriksson et al., 2017; Nawrot & Doucet, 2014; Wang et al., 2023). Learners in CE usually have to balance learning with concurrent commitments, such as family or professional commitments, and may, therefore, have limited time available for learning (Eriksson et al., 2017; Schröer et al., 2022). Thus, ALEs that aim at supporting learners' self-regulation and efficient usage of their time resources might be beneficial for CE. Consequently, several interventions identified in Study 2 (e.g., individual reminders, recommendation of learning resources based on available time) aim at supporting learners' SRL strategies or personalizing CE activities based on learners' time resources.

In Study 2, participants mentioned several interventions based on indicators of internal conditions (e.g., adaptation of the general difficulty level and thematic focus) as well as interventions based on indicators of external conditions (e.g., recommendation of learning resources relevant to the working area). For some indicators from Study 1 (e.g., parent's level of education, reputation), no interventions were identified, which might indicate that not all indicators are equally suitable and relevant to designing ALEs for CE. Moreover, participants mentioned several task-loop (e.g., recommendation of goal-oriented learning) and step-loop (e.g., prompts for specific learning strategies) interventions addressing differences between learners. Only one design-loop intervention (adaptive group size) addressing similarities between learners was mentioned. This might indicate a stronger need for personalized learning than for design-loop interventions in CE. However, the low number of design-loop interventions might also be due to the introduction to ALEs given to participants at the beginning of the focus group interviews, where examples focused predominantly on interventions to personalize learning rather than interventions addressing similarities between learners.

Some of the interventions (e.g., recommendation of learning partners, individual reminders) identified in Study 2 are similar to those identified in Schumacher and Ifenthaler's (2018) study for the higher education context. Others (e.g., adaptation of the general difficulty level and thematic focus, context adaptation, recommendation of learning resources relevant to the working area, recommendation of learning resources based on available time) seem to be more specific for CE. ALEs that tailor learning activities to learners' prior experiences and knowledge, everyday (work) tasks, and time resources seem to be more relevant in CE than in higher education. This is in line with adult learning theory (Knowles, 1985; Knowles et al., 2012), which suggests that learners in CE tend to be more heterogeneous in their prior experiences and knowledge than learners in higher education (Knowles et al., 2012; Meister & Willyerd, 2021). Therefore, ALEs that take into account learners' prior experiences and knowledge may be particularly beneficial for CE (Wozniak, 2020). Moreover, adult learning theory suggests that learners in CE need clear reasons why they should invest their limited time in CE and want to understand how the learning activities benefit them in their daily (work) life (Knowles et al., 2012; Wozniak, 2020). Therefore, interventions that highlight the personal benefits of the learning activities, such as context adaptation or recommendation of learning resources relevant to the working area, and consider learners' time resources are needed for CE.

Study 3 represents the first study evaluating different interventions for ALEs for CE in terms of learners' willingness to use, perceived learning support, as well as technological and organizational implementation effort. The study complements Schumacher et al.'s (2019) study that evaluated interventions for the higher education context. While in Schumacher et al.'s (2019) study, self-assessments, learning recommendations, and revisions of former learning content were the most highly evaluated interventions in terms of learners' willingness to use and perceived learning support, adaptation of the general difficulty level and thematic focus was the most highly evaluated intervention by learners in our study. These findings again highlight the need for adaptivity to learners' heterogeneity in prior experiences and knowledge in CE (Knowles et al., 2012; Meister & Willyerd, 2021). However, according to the findings from Study 3, the interventions most highly prioritized by learners seem to require higher implementation efforts. According to the evaluations of the CE and educational technology specialists, step-loop interventions consisting of notifications or visualizations (e.g., individual countdowns, individual reminders, dashboards) have the lowest implementation effort. This estimate of the implementation effort is consistent with Schumacher et al.'s (2019) findings, where reminders for deadlines and rating scales were considered to have the lowest implementation effort.

3.9.2 Limitations and Future Research

Our study is subject to some limitations that may provide implications for future research. First, although Study 1 provides a comprehensive list of potential indicators for ALEs for CE, we did not analyze how these indicators can be validly measured by ALEs. Therefore, future research should investigate methods for measuring the identified indicators in online learning settings. These methods may, for example, include self-report questionnaires as well as trace data (Araka et al., 2020; Gašević et al., 2016; Xie et al., 2019). However, for a valid use of trace data, trace data still needs to be firmly anchored in learning theory, and valid frameworks for measuring theoretical constructs using trace data still need to be developed (Giannakos & Cukurova, 2023; Kaliisa et al., 2022; Marzouk et al., 2016).

Second, the descriptions of the interventions identified in Study 2 are superficial and represent first ideas rather than detailed implementation plans. This might also have influenced participants' evaluations in Study 3, as participants might have had different perceptions of the interventions. Future research should elaborate on the interventions identified in this paper and investigate how exactly they should be designed for the context of CE.

Third, the findings of our studies may be subject to some biases. Self-selection bias (Heckman, 1990) might have occurred, as predominantly learners motivated for CE, as well as learners and specialists interested in ALEs, might have decided to participate in our studies. In addition, our findings rely solely on learners' conscious experiences. Since informal CE may also occur through unconscious learning activities (Eraut, 2004; Schiersmann, 2007; Schumacher, 2018), indicators relevant to informal CE might have been overlooked in Study 1. Although some interventions identified in Study 2 may be applied to formal, non-formal, and informal CE (e.g., recommendation of learning partners, dashboards), further investigations regarding different types of CE are needed. Future research should elaborate on how our interventions can be applied to different types of CE and how ALEs can be used to support informal CE.

Fourth, as the studies presented in this paper do not represent experiments, no statements about causality can be made. Our findings do not allow us to draw any conclusions about the effectiveness of ALEs in supporting learning processes in CE. Therefore, future research should implement the interventions identified in this paper and evaluate them in experimental settings.

3.9.3 Practical Implications

Our paper provides a sound basis for designing ALEs for CE, as it provides an empirical list of indicators and interventions that are relevant to CE. The framework presented in Figure 3-3 may help researchers, system designers, as well as CE and educational technology specialists find appropriate interventions for a specific learning context by following the following two steps:

(1) From the framework, identify the indicators most relevant to the specific learning context. These may be indicators that have the strongest influence on desired learning processes and outcomes or indicators with the greatest heterogeneity between learners (Plass & Pawar, 2020b).

(2) Find the intervention(s) in the framework that address(es) the indicator(s) identified in step (1) and consider learners' and specialists' evaluations of these interventions.

For example, when designing a CE activity for a target group of learners for whom the limited time they have available for learning is expected to be the biggest challenge to learning (Eriksson et al., 2017; Schröer et al., 2022), the interventions for the indicator *time available for learning* in our framework might be appropriate. Further, when designing a CE activity for a target group of learners who might especially differ with regard to prior knowledge (Rasch & Middelbeck, 2022), the intervention for the indicator *prior knowledge* might be appropriate. Moreover, the evaluations in terms of learners' willingness to use the interventions and perceived learning support, as well as technological and organizational implementation effort, may be used to prioritize interventions and to assess the benefits and challenges associated with different interventions. When implementing ALEs for CE, the benefits and implementation challenges of specific interventions must be thoroughly weighed to determine whether the intervention may be advantageous and feasible (Schumacher et al., 2019).

While most existing ALEs for CE are not based on empirical findings and do not consider different user perspectives or learning theories (Bernacki et al., 2021; Chaipidech et al., 2022), our studies integrate empirical findings on different stakeholders' (i.e., learners', CE specialists', and educational technology specialists') perspectives into the design of ALEs. Hence, our studies help to move the design of ALEs from a data-driven to a more user-centered and empirically-based perspective. By providing an empirical rationale for selecting indicators and interventions, our studies may help design trustworthy ALEs that meet learners' specific needs and overcome technological and organizational challenges when implementing ALEs in CE practice (Fake & Dabbagh, 2020; Schumacher & Ifenthaler, 2018). Thus, our studies may represent a starting point for a comprehensive implementation of ALEs in CE.

3.9.4 Conclusion

In today's rapidly changing (working) world, where individuals are constantly required to participate in CE activities, ALEs represent a promising invention for personalizing and supporting learning processes (Hemmler & Ifenthaler, 2022b; Manuti et al., 2015). To successfully implement ALEs in CE, different stakeholders' perspectives on ALEs need to be considered (Fake & Dabbagh, 2020; Schumacher & Ifenthaler, 2018). Therefore, this paper investigated different stakeholders' (e.g., learners', CE specialists', and educational technology specialists') perspectives on indicators and interventions for ALEs for CE. Several indicators related to learners' internal and external conditions (Winne, 2022; Winne & Hadwin, 1998), as well as corresponding interventions for personalizing and supporting learning processes, were identified. A framework classifying interventions based on indicators and adaptivity type (Aleven et al., 2017), as well as providing different stakeholders' evaluations of interventions, was developed. This framework can be used by researchers, system designers, as well as CE and educational technology specialists to design user-centered and trustworthy ALEs for CE. In this regard, future research should implement and evaluate the interventions identified in our framework to investigate the effectiveness of ALEs in supporting learning processes in CE.

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4. Paper 2: Technology-Enhanced Personalized Learning Environments Based on Prior Knowledge in Continuing Education: An Experimental Study

4.1 Introduction

Technology-enhanced personalized learning environments based on prior knowledge (TEPLEs-PK) have been considered a promising invention for continuing education (CE; Rasch & Middelbeck, 2022; Wozniak, 2020). CE is a central element of lifelong learning and important for keeping knowledge, skills, and competences up-to-date (Mlambo et al., 2021; Omar et al., 2024). While learners in CE usually differ in their (professional) backgrounds and prior experiences and may enter a CE activity with varying levels of prior knowledge (Knowles et al., 2012; Meister & Willyerd, 2021), TEPLEs-PK may create learning opportunities that consider individual learners' prerequisites (Chaipidech et al., 2022; Omar et al., 2024). TEPLEs-PK tailor learning activities to individual learners' prior knowledge, aiming at presenting the best next learning content to be learned by the individual learner in order to master a particular learning topic (Al-Chalabi et al., 2021; Chaipidech et al., 2022; Rasch & Middelbeck, 2022). They may prevent learners both from being overwhelmed by the learning content and from inefficiently using their time on learning content they have already mastered (Alshammari & Qtaish, 2019; Rasch & Middelbeck, 2022).

However, although researchers have emphasized the potential of TEPLEs-PK for CE (Chaipidech et al., 2022; Rasch & Middelbeck, 2022), experimental studies evaluating TEPLEs-PK in the context of CE are scarce (Teich et al., 2024), and the effectiveness of TEPLEs-PK in supporting learning processes in CE remains unclear. Moreover, little is known about how individual factors impact the effectiveness of TEPLEs-PK in supporting learning processes in CE. Research has shown that individual factors, such as learners' motivational dispositions, may impact the effectiveness of pedagogical interventions (Duffy & Azevedo, 2015; Y. Wang et al., 2024). Therefore, learners might differ in their perceptions of TEPLEs-PK, and different learners might benefit from different types of (personalized) learning support (Beheshitha et al., 2016; Lallé et al., 2016; Schumacher & Ifenthaler, 2018).

Thus, further research is needed to understand the effects of TEPLEs-PK on learning outcomes in CE, as well as to identify individual factors impacting the effectiveness of TEPLEs-PK in supporting learning processes in CE. Such insights may help design advantageous TEPLEs-PK for CE and identify individuals for whom TEPLEs-PK may provide effective learning support (Zheng et al., 2022). Therefore, this study aims to investigate the effects of TEPLEs-PK on learning outcomes in CE, as well as how learners' motivational dispositions (i.e., goal orientations and task value) moderate these effects.

4.2 Personalized Learning Based on Prior Knowledge

Prior knowledge has been defined as domain-specific information stored in a learner's long-term memory before the onset of the learning process (Bittermann et al., 2023; Simonsmeier et al., 2022; Song et al., 2016) and may include both declarative (knowing what) and procedural (knowing how) knowledge (Winterton et al., 2005). Prior knowledge refers to information related to subsequent learning content and differs from knowledge that is assessed during or after the delivery of the learning content to which it relates (Alonso et al., 2025; Fariani et al., 2023).

When completing learning tasks, learners try to connect new information to their prior knowledge (Song et al., 2016; van Gog et al., 2005). Thus, learners' individual level of prior knowledge may influence learning outcomes (Baek et al., 2015; Simonsmeier et al., 2022). On the one hand, prior knowledge may positively affect learning performance (Baek et al., 2015) and learner satisfaction (Shangguan et al., 2020) by facilitating information encoding and knowledge acquisition (Baek et al., 2015; Simonsmeier et al., 2022). However, on the other hand, learning activities that only cover what learners already know may also impair learning by guiding learners' attention to content they have already mastered, preventing them from processing new ideas and perspectives (Brod, 2021; Simonsmeier et al., 2022). Hence, researchers have emphasized the need for personalized learning environments that tailor learning activities to individual learners' prior knowledge, aiming to neither over- nor underchallenge learners and helping them to build on what they already know (Al-Chalabi et al., 2021; Chaipidech et al., 2022; Rasch & Middelbeck, 2022).

In order to personalize learning activities, prior knowledge may be assessed using historical data (e.g., previously completed learning activities, learners' educational level; Xue-jun et al., 2021; Yau & Ifenthaler, 2020) or diagnostic tests where learners either have to self-report their prior knowledge or complete a knowledge test (Al-Chalabi et al., 2021; Chaipidech et al., 2022). Based on learners' prior knowledge, learning activities may be personalized by adapting the difficulty level of the learning content (e.g., Al-Chalabi et al., 2021; Raj & Renumol, 2024), by skipping learning content already known to the learner (e.g., Alshammari et al., 2015; Alshammari & Qtaish, 2019), by offering personalized learning paths (e.g., M. Liu et al., 2017; Niknam & Thulasiraman, 2020), or by providing personalized recommendations of learning content (e.g., Pal et al., 2024; Teich et al., 2024). However, identifying the best learning content based on individual learners' prior knowledge in order to provide personalized learning experiences is a complex endeavor that may depend not only on learners' prior knowledge but also on their motivational dispositions (Basavaraj & Garibay, 2018; Schumacher & Ifenthaler, 2018).

4.3 The Moderating Role of Motivational Dispositions

Motivation is a multi-faceted construct that describes initiating and maintaining goal-directed activities (Pintrich & Schunk, 2002). Motivation is a key driver of learning performance (Robbins et al., 2004) and may influence learners' perceptions of their learning processes, as well as their learning strategies and preferences (Eom, 2019; Wolters, 2004). Based on their motivational dispositions, such as their goal orientations and task value, learners may prefer either challenging tasks that help them learn something new or tasks that focus on learning content they have already mastered (Basavaraj & Garibay, 2018; Urdan & Kaplan, 2020).

4.3.1 Goal Orientations

Goal orientations refer to the objectives or reasons why learners engage in achievement tasks and the criteria they choose to evaluate their success in achievement tasks (Pintrich, 2000a). Goal orientations consist of a set of attributions, beliefs, and affects that determine learners' motivation, as well as achievement-related behaviors and preferences (Ames, 1992; Urdan & Kaplan, 2020; Wolters, 2004). In the course of the history of goal orientation research, researchers have proposed different models of goal orientations that slightly differ in the number and labeling of the goal orientations that learners may pursue (e.g., Ames, 1992; Dweck, 1986; Elliot, 1999; Elliot et al., 2011; Spinath et al., 2012; Urdan & Kaplan, 2020). In this paper, we focus on the work of Spinath et al. (2012), who proposed four types of goal orientations: mastery goal orientation, performance-approach goal orientation, performance-avoidance goal orientation, and work-avoidance goal orientation.

Learners with a strong mastery goal orientation strive for personal growth and to increase their knowledge, skills, and competences (Elliot, 1999; Kaplan & Maehr, 2007; Spinath et al., 2012; Wolters, 2004). They define success in achievement tasks as meeting either task-related criteria (e.g., performing the task correctly) or intrapersonal criteria (e.g., performing the task better than in the past; Elliot, 1999; Senko et al., 2011). Thus, the stronger learners' mastery goal orientation, the more they may appreciate learning content that they have not yet mastered and challenging tasks that help them learn something new (Basavaraj & Garibay, 2018; Schumacher & Ifenthaler, 2018).

In contrast, learners pursuing a strong performance-approach goal orientation strive to demonstrate their knowledge, skills, and competences or outperform others in achievement tasks (Dweck, 1986; Kaplan & Maehr, 2007; Senko et al., 2011; Spinath et al., 2012; Wolters, 2004). They define success in achievement tasks as meeting interpersonal criteria and showing their competence (e.g., getting the best grade in the course; Elliot, 1999; Senko et al., 2011). Learners pursuing a strong performance-avoidance goal orientation focus on avoiding negative judgments on their knowledge, skills, and competences, as well as on not appearing dumb (Kaplan & Maehr, 2007; Pintrich, 2000b; Spinath et al., 2012; Wolters, 2004). They define success as meeting interpersonal criteria and avoiding showing their incompetence (e.g., not getting the worst grade in the course; Elliot, 1999; Senko et al., 2011). Thus, the stronger learners' performance-approach or performance-avoidance goal orientation, the more they may prefer to focus on learning content they have already mastered to demonstrate their knowledge, skills, and competences or to avoid negative judgements (Basavaraj & Garibay, 2018; Senko et al., 2011; Spinath et al., 2012).

Finally, learners with a strong work-avoidance goal orientation focus on completing achievement tasks with the least possible effort and avoiding challenging tasks (King & McInerney, 2014; Spinath & Schöne, 2019; Spinath et al., 2012). They define success in achievement tasks as minimal expenditure of effort and work (King & McInerney, 2014). Since learning tasks related to learners' prior knowledge may require less effort than learning tasks containing new information (Brod, 2021; Dong et al., 2020), learners with a strong work-avoidance goal orientation may prefer to focus on learning content they have already mastered. However, learners with a strong work-avoidance goal orientation may also appreciate personalized learning environments that allow them to skip learning content based on their prior knowledge (Rasch & Middelbeck, 2022), as skipping learning content minimizes the expenditure of effort and work (King & McInerney, 2014; Rasch & Middelbeck, 2022; Spinath & Schöne, 2019).

4.3.2 Task Value

Task value refers to learners' perceptions of how personally important, interesting, and useful an achievement task is (Eccles, 1983; Eccles & Wigfield, 2020, 2023; Pintrich et al., 1993; Wigfield & Eccles, 2000). Task value is a key component of achievement motivation and may influence achievement-related behaviors and preferences (Eccles & Wigfield, 2020, 2023; Shang et al., 2023; Wigfield & Eccles, 2000). Research has shown that task value is positively related to learning engagement (Shang et al., 2023; Vo & Ho, 2024), effort (Dietrich et al., 2017; F. Wu et al., 2020), and persistence (Shang et al., 2023). Thus, learners with a strong task value may be willing to spend time on learning content because they perceive the content as important, interesting, or useful, regardless of their prior knowledge (Eccles & Wigfield, 2020; Vo & Ho, 2024). Thus, learners' task value may weaken the effects of prior knowledge on learning outcomes (Baek et al., 2015) and reduce the need for personalization based on prior knowledge.

4.4 The Need for Personalized Learning in Continuing Education

CE refers to a broad variety of 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 the completion of an initial phase of education (e.g., after the completion of a university degree; Demary et al., 2013; *Further and Higher Education Act*, 1992; Schiersmann, 2007). Researchers have argued that learners in CE are characterized by their unique life experiences (Knowles, 1985; Knowles et al., 2012). Compared to learners in K-12 and higher education, learners in CE have a greater quantity and quality of life experiences and, therefore, tend to be more heterogeneous regarding their prior knowledge and motivational dispositions (Knowles et al., 2012; Meister & Willyerd, 2021; Wozniak, 2020). Consequently, researchers have recognized the need for personalized learning in CE and argued that one-size-fits-all approaches, which ignore the heterogeneity of learners in CE, may suffer from high dropout rates and impaired learning performance (Al-Chalabi et al., 2021; Rasch & Middelbeck, 2022; W. Wang et al., 2023).

With the increasing use of educational technologies and the rise of CE activities offered online, the need for personalized learning has become more prominent (K. C. Li & Wong, 2023; Omar et al., 2024). Online learning offers access to learning opportunities for a diverse range of learners, regardless of time and location (Meyer et al., 2023). Therefore, the heterogeneity of learner characteristics may be even greater in online learning than in (classroom-based) face-to-face learning settings (Rasch & Middelbeck, 2022).

Moreover, lack of time has been identified as a main barrier to CE and a common reason for dropout from CE (da Luz et al., 2018; Eriksson et al., 2017; Nawrot & Doucet, 2014; W. Wang et al., 2023). Learners in CE usually have to balance learning with concurrent commitments, such as family and professional commitments, limiting the time they have available for learning (da Luz et al., 2018; Eriksson et al., 2017; Schröer et al., 2022). Hence, effective learning environments for CE should consider learners' individual level of prior knowledge and prevent learners from spending unnecessary time on learning content they have already mastered (Chaipidech et al., 2022; Rasch & Middelbeck, 2022).

4.5 Technology-Enhanced Personalized Learning Environments Based on Prior Knowledge in Continuing Education

The increasing use of educational technologies and online learning opportunities has not only increased the need for personalized learning to consider the heterogeneity of the learner base (Rasch & Middelbeck, 2022) but also offered new opportunities for personalizing learning processes (Fariani et al., 2023; K. C. Li & Wong, 2023; Omar et al., 2024). Educational technologies enable the collection and storage of large amounts of education-related data that may provide useful insights into learner characteristics and be leveraged to personalize learning processes (Fariani et al., 2023; Hemmler & Ifenthaler, 2022). Consequently, researchers have begun to develop TEPLEs-PK for CE. For example, Xue-jun et al. (2021) developed a learning path recommendation system for military CE that generates a personalized study plan based on learners' answers in a diagnostic knowledge test. Further, Chaipidech et al. (2022) introduced a mobile application for teacher CE that provides personalized recommendations of learning content based on learners' performance in a diagnostic knowledge test. Teich et al. (2024) developed a personalized learning system that highlights relevant learning content based on individual learners' prior knowledge and provides personalized estimations of the learning times needed to complete learning content. Moreover, Rasch and Middelbeck (2022) introduced a learning platform for CE that uses knowledge graphs to predict learners' prior knowledge based on a short diagnostic test and allows learners to skip learning content they have already mastered.

TEPLEs-PK aim to optimize learning experiences by enhancing the fit between learner and learning activities (Omar et al., 2024; Rasch & Middelbeck, 2022). Therefore, researchers have assumed that TEPLEs-PK would positively affect learning outcomes in CE, such as course completion or learning performance (Al-Chalabi et al., 2021; Chaipidech et al., 2022; Rasch & Middelbeck, 2022). However, we suggest that there are at least three reasons why empirical evidence regarding the effectiveness of TEPLEs-PK in supporting learning processes in CE is lacking:

First, most researchers introducing TEPLEs-PK for CE either did not empirically evaluate the effects of their learning systems on learning outcomes (e.g., Xue-jun et al., 2021) or did not use a control group design (e.g., Chaipidech et al., 2022). To our knowledge, Teich et al.'s (2024) study is the only study that evaluated the effects of TEPLEs-PK on learning outcomes in CE using a control group design. Teich et al.'s (2024) learning system, which provides personalized highlighting of learning content and personalized estimations of learning times based on learners' prior knowledge, improved learners' environmental structuring but had limited effects on learning performance. Moreover, Teich et al.'s (2024) learning system included an additional intervention (a structured course overview) that was not based on prior knowledge, and it remains unclear whether the effects found in the study were caused by this intervention or by the personalization based on prior knowledge. Further, experimental studies have shown positive effects of personalized learning environments that tailor learning activities to individual learning behavior on knowledge increase (Rosen et al., 2018) and learning progress (Tzeng et al., 2024) in MOOCs, as well as positive effects of TEPLEs-PK on exam scores in higher education (Arsovic & Stefanovic, 2020; Niknam & Thulasiraman, 2020). However, the findings of these studies can only be applied to TEPLEs-PK in CE with reservations, as they either did not focus on personalization based on prior knowledge (Rosen et al., 2018; Tzeng et al., 2024) or did not focus on CE but on higher education (Arsovic & Stefanovic, 2020; Niknam & Thulasiraman, 2020).

Second, the effects of TEPLEs-PK on learner satisfaction in CE have been largely overlooked in previous research (e.g., Chaipidech et al., 2022; Teich et al., 2024). Since learners in CE are characterized by a strong need for self-direction (Knowles, 1985; Knowles et al., 2012; Manning, 2007), learner satisfaction may influence learners' continuance intention, engagement, and future participation in CE activities (Daneji et al., 2019; Y. Liu et al., 2023; Y.-C. Wu et al., 2015). Therefore, understanding the effects of TEPLEs-PK on learner satisfaction in CE is crucial for creating positive learning experiences (Daneji et al., 2019; Du, 2023). Since TEPLEs-PK aim at selecting the best learning content for the individual learner, they should help avoid negative affects such as overburdening or boredom and, in turn, enhance learner satisfaction (Bernacki et al., 2021; K. C. Li & Wong, 2023; Omar et al., 2024). In previous studies, learners showed positive attitudes towards personalized learning environments (Alamri et al., 2020; Fromm & Ifenthaler, 2024; Xu et al., 2024). However, experimental studies evaluating the causal effects of TEPLEs-PK on learner satisfaction in CE are missing.

Third, little is known about the variables moderating the effects of TEPLEs-PK on learning outcomes. Since researchers have argued that different learners may benefit from different types of (personalized) learning support (Schumacher & Ifenthaler, 2018; Y. Wang et al., 2024), identifying variables that moderate the effects of TEPLEs-PK on learning outcomes in CE is crucial for developing beneficial TEPLEs-PK for CE. In Schumacher and Ifenthaler's (2018) study, goal orientations were related to learners' perceived support from learning analytics in higher education. Moreover, research has shown that goal orientations moderate the effects of personalized feedback and prompts (Duffy & Azevedo, 2015; Lallé et al., 2016) and personalized dashboards (Beheshitha et al., 2016) on learning outcomes in online and blended learning environments. Empirical studies further revealed positive relationships between task value and learners' engagement with personalized learning support (Butler & Lumpe, 2008; Cornelisz & van Klaveren, 2018). However, studies investigating whether goal orientations and task value moderate the effects of TEPLEs-PK on learning outcomes in CE are missing.

4.6 Overview of the Present Study

4.6.1 edyoucated-Platform

The edyoucated platform (https://edyoucated.org/) introduced by Rasch and Middelbeck (2022) was investigated in the present study. The edyoucated-platform is an online learning platform for CE that aims to support (corporate) learning and development processes through personalized learning experiences. For the work at hand, the element of interest of the edyoucated-platform is its ability to personalize a learning path based on individual learners' prior knowledge. A learning path (e.g., Microsoft Excel, Data Reporting, Project Management) on the edyoucated-platform consists of an ordered collection of learning materials (e.g., texts, videos, quizzes), which represent small learning entities with a respective learning time of only a few minutes each and are grouped into small units of learning artifacts called skill atoms (see Figure 4-1).

The goal of the personalization system of the edyoucated-platform is to let learners skip the skill atoms that they have already mastered prior to starting the learning path, such that the number of skill atoms and related learning materials decreases with increasing prior knowledge, and the learning path becomes shorter. Hence, a key task of the personalization system is to assess learners' prior knowledge by figuring out which skill atoms a learner has already mastered. The assessment of a skill atom can be done in two variants: a self-report question or a knowledge question (see Figure 4-2). In the former variant, learners are prompted to answer a direct question about their prior knowledge with either "Yes", "Maybe", or "No". If the answer is "Yes", the system considers the skill atom as mastered, whereas both "Maybe" and "No" are translated into unmastered. In the latter variant, learners are prompted to answer a question that can be answered correctly or incorrectly. If the question is answered correctly, the skill atom is assumed to be mastered; otherwise, it is assumed to be unmastered.

Figure 4-1

Overview of the Microsoft Excel Learning Path on the edyoucated-Platform

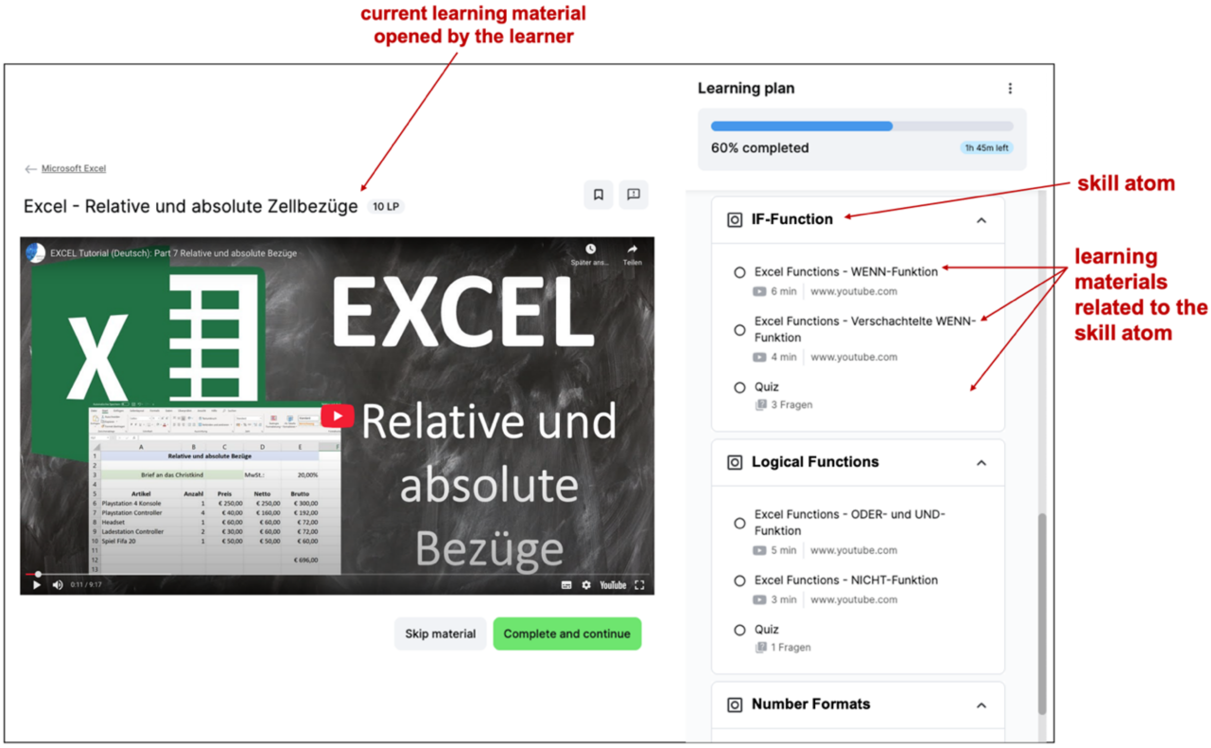


Figure 4-2

Assessment of a Skill Atom

Self-report question:

Do you know how to use **logical functions** in Excel?

- ○ **Yes**, definitely
- ○ **Maybe**, I am not sure
- ○ **No**, not really

Knowledge question:

Please check all correct answers.

In an Excel sheet including employee information, you want to identify employees that did not comply with at least one of the following criteria: completion of a mandatory training course, performance evaluation of at least 3, less than 5 sick days. Information on the completion of the training course are presented in column A, the performance evaluation in column B, and the number of sick days in column C of the Excel sheet. Which formula can identify whether the employee in row 2 of the Excel sheet does not comply with at least one of the criteria?

- ☐ A. =NOT(OR(A2="completed", B2<3, C2>5))
- ☐ B. =OR(NOT(A2="completed", B2>=3, C2<=5))
- ☐ C. =NOT(AND(A2="completed", B2>=3, C2>5))
- ☐ D. = NOT(AND(A2="completed", B2>=3, C2<5))

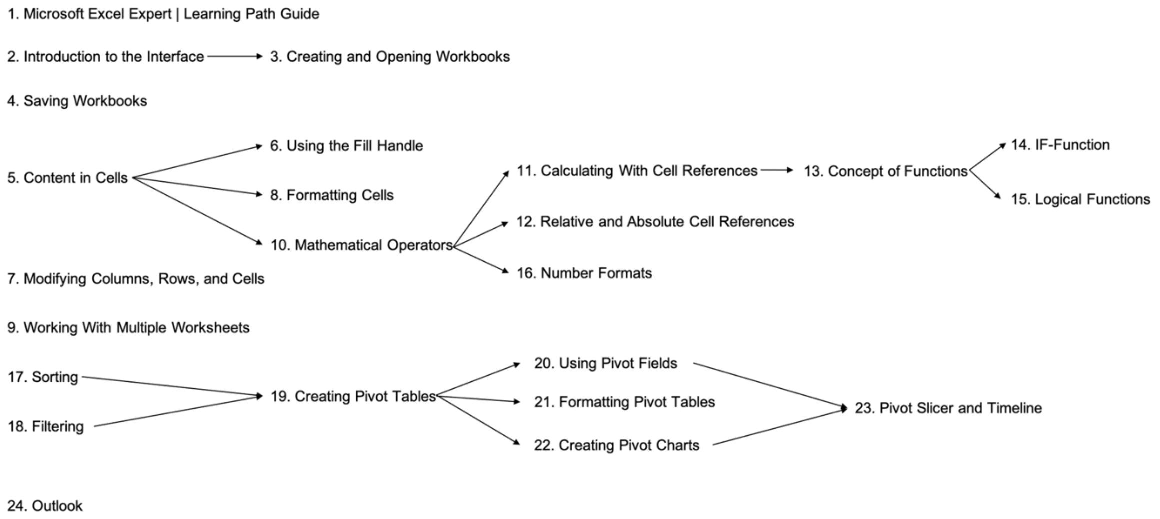
A basic idea would be to prompt learners to answer one (self-report or knowledge) question for each skill atom within a learning path to determine which skill atoms a specific learner has already mastered. However, since skill atoms represent very small units of learning artifacts (with related learning materials with only a few minutes each), the personalization occurs at a very granular level, and a learning path on the edyoucated-platform may consist of up to one hundred skill atoms. Thus, depending on the learning path, asking a question for each skill atom may imply a lengthy and time-consuming assessment process that may frustrate and bore learners (Han & Fan, 2020). Therefore, the idea of the personalization system is to predict learners' prior knowledge regarding all skill atoms of a learning path with as few assessment questions as possible.

The personalization system of the edyoucated-platform is based on the concept of knowledge structures introduced by Falmagne and Doignon (2011). It assumes that the different skill atoms of a learning path are not entirely unrelated, but that they are connected via learning prerequisite relationships: To understand, learn, and master a certain skill atom, other skill atoms (the prerequisites) must be mastered before. The skill atoms and their relationships form a directed knowledge graph with two immediate implications: For all unmastered skill atoms, we can deduce that all subsequent dependent skill atoms cannot have been mastered either. For all mastered skill atoms, we can deduce that all prerequisites must have also been mastered. Figure 4-3 illustrates the relationships between the skill atoms of the Microsoft Excel learning path employed in the present study. For example, if an assessment question indicates that a specific learner has not yet mastered the skill atom "Creating Pivot Charts", we can deduce that this learner has not mastered the skill atom "Pivot Slicer and Timeline" either. In contrast, if the assessment question indicates that the learner has mastered the skill atom "Creating Pivot Charts", we can deduce that the learner has also mastered the skill atoms "Sorting", "Filtering", and "Creating Pivot Tables".

The assessment strategy implemented by the personalization system is to continuously ask for the most discriminating skill atom, that is, the skill atom that (in expectation) delivers the most additional information about the other skill atoms in the knowledge graph. This approach allows a quick assessment of learners' prior knowledge to personalize the learning path. The knowledge graphs describing the relationships between the skill atoms of a learning path can either be modeled manually by domain experts or trained based on assessment data from previous learners. For the learning path used in the present study, the knowledge graph was modeled manually by domain experts. For a more detailed description of the creation of knowledge graphs, we refer to the prior work of Rasch and Middelbeck (2022).

Figure 4-3

Overview of the Relationships Between the Skill Atoms of the Microsoft Excel Learning Path



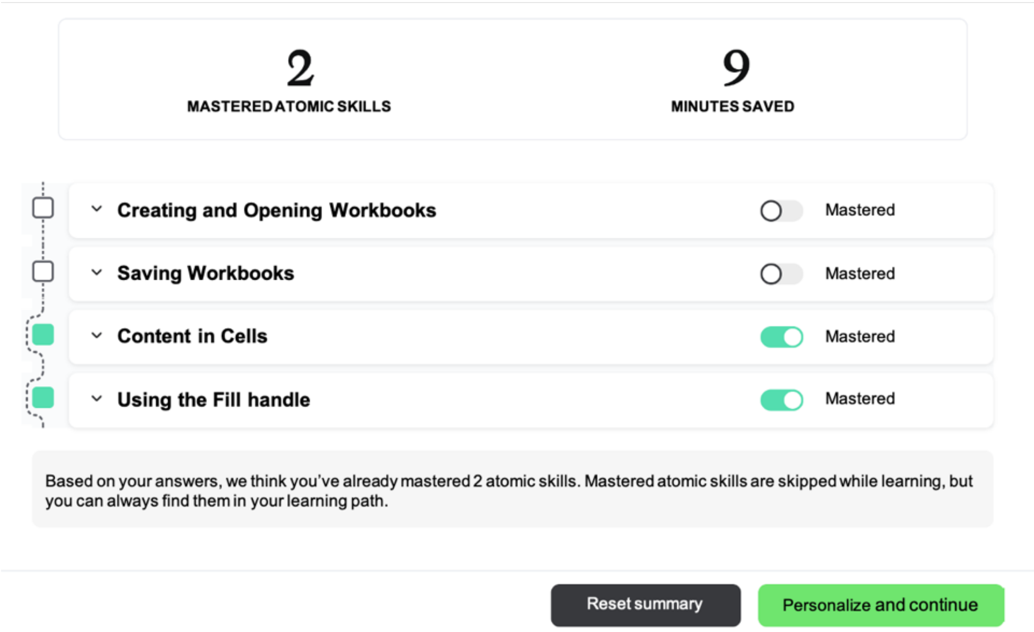
Note. The numbers indicate the order in which the skill atoms are presented to the learner within the learning path. Even though the skill atoms are presented in a linear order, the prerequisite relationships between skill atoms do not form a linear chain. That is, prerequisite relationships between skill atoms can extend across the full knowledge graph and not just between subsequent skill atoms according to their presentation within the learning path.

To allow learners to start their learning process as quickly as possible, the assessment of learners' prior knowledge is performed incrementally. That is, instead of asking all the questions necessary to predict learners' prior knowledge of the entire learning path at the beginning of the learning path, the assessment is started with a few questions at the start of the learning path and then continuously mixed into the path. Thus, different assessment elements containing a maximum of five assessment questions each are alternated with learning materials. All assessment elements measure learners' prior knowledge regarding the subsequent skill atoms in the learning path.

After each assessment element, learners receive a short summary of the assessment results and the skill atoms that they are allowed to skip based on their prior knowledge (see Figure 4-4). This summary includes an overview of the assessment results of all skill atoms that were addressed directly by the assessment questions asked in the assessment element, as well as the assessment results of all further skill atoms that can be derived from these questions based on their relationships in the knowledge graph. Learners can use the assessment summary to correct the assessment by switching specific skill atoms from mastered to unmastered or vice versa, which in turn corrects the generated personalized learning path. The skill atoms identified as mastered are marked as such within the learning path. In contrast to unmastered skill atoms, learners can skip these skill atoms and do not need to complete them in order to progress in the learning path. However, the skill atoms identified as mastered do not completely disappear from the learning path, and learners can still see and work with the related learning materials if they want to. Even though the assessment strategy of the edyoucated-platform has been shown to be accurate (Rasch & Middelbeck, 2022), it is possible that predictions may contradict learners' actual prior knowledge (e.g., because the knowledge graph does not exactly represent the actual relationships between the skill atoms or because learners misunderstand the meaning of the assessment question). Therefore, the edyoucated-platform allows learners to correct the assessment results and does not remove the skill atoms identified as mastered. Moreover, these approaches enhance learner autonomy, which may positively affect learner motivation and engagement (Deci et al., 1996; Knowles et al., 2012; Schumacher, 2018; Wozniak, 2020).

Figure 4-4

Assessment Summary



4.6.2 Experimental Conditions

To evaluate the personalization system of the edyoucated-platform, we compared three different experimental conditions:

(1) Personalization based on self-report questions (PSRQ) condition: The personalization system of the edyoucated-platform was activated, whereby the assessment of learners' prior knowledge was based on self-report questions.

(2) Personalization based on knowledge questions (PKQ) condition: The personalization system of the edyoucated-platform was activated, whereby the assessment of learners' prior knowledge was based on knowledge questions.

(3) Control condition: Learners followed a static version of the learning path. That is, the personalization system of the edyoucated-platform was not activated, no assessment of learners' prior knowledge occurred, and learners were not allowed to skip skill atoms.

4.6.3 Hypotheses

Effects on Learning Outcomes

The personalization system of the edyoucated-platform aims to help learners save learning time by skipping learning content based on their prior knowledge. However, such systems can only be considered beneficial if skipping learning content does not negatively affect learners' knowledge increase during the learning period (Alshammari & Qtaish, 2019; Arsovic & Stefanovic, 2020). Since the skill atoms that may be skipped represent learning content already known to the learner, we suggest that the knowledge increase during the learning period is not lower in the personalized (PSRQ and PKQ) conditions than in the control condition (Hypothesis 1). Moreover, since the personalization system of the edyoucated-platform may reduce the amount of learning materials within a learning path based on learners' prior knowledge and aims to enhance the fit between learner and learning content, it might prevent dropout and enhance learner satisfaction (Alamri et al., 2020; Rasch & Middelbeck, 2022). Therefore, we suggest that learners in the personalized (PSRQ and PKQ) conditions should be more likely to complete their learning path (Hypothesis 2) and be more satisfied with their learning process (Hypothesis 3) than learners in the control condition.

The Moderating Role of Motivational Dispositions

As discussed in Section 4.3, depending on their goal orientations and task value, learners may prefer to focus either on learning content that helps them learn something new or on learning content they have already mastered (Basavaraj & Garibay, 2018; Urdan & Kaplan, 2020). Therefore, learners' motivational dispositions may impact the effectiveness of the personalization system of the edyoucated-platform. We suggest that learners' goal orientations (Hypothesis 4) and task value (Hypothesis 5) moderate the effects of the experimental condition on (a) knowledge increase, (b) learning path completion, and (c) learner satisfaction.

4.7 Method

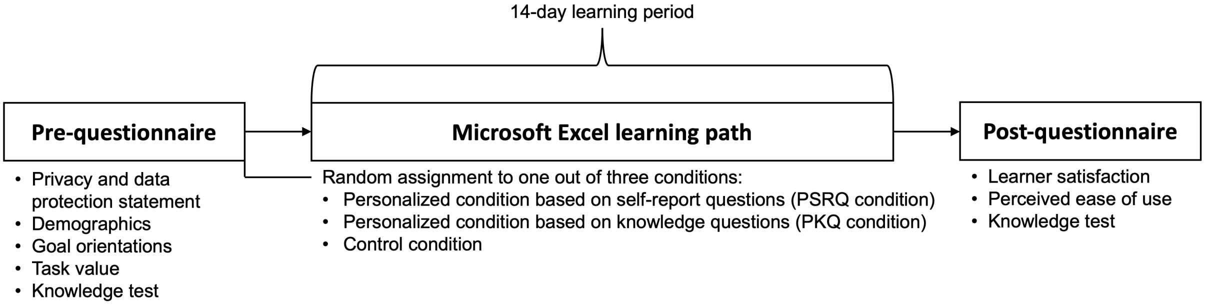
4.7.1 Research Design and Procedure

We conducted a study with a between-subjects design. Participants were invited to complete a Microsoft Excel learning path on the edyoucated-platform and were randomly assigned to one of the three experimental conditions mentioned in Section 4.6.2 (PSRQ, PKQ, or control condition). The Microsoft Excel learning path consisted of 24 skill atoms ranging from very basic Microsoft Excel functionalities (e.g., creating and opening workbooks) to advanced topics (e.g., creating pivot charts). The skill atoms were presented in an ordered collection, starting with the basic and ending with the advanced topics. The learning materials related to the skill atoms had a total learning duration of approximately 3.5 hours and were identical across all three conditions. However, in the two personalized conditions, the assessment questions (i.e., self-report questions in the PSRQ condition and knowledge questions in the PKQ condition) related to the personalization system were alternated with the learning materials, and learners were allowed to skip skill atoms based on their answers in the assessment questions. The first and last skill atom (1. Microsoft Excel Expert | Learning Path Guide, 24. Outlook, see Figure 4-3) were mandatory; that is, they could not be skipped in the personalized conditions either (they represented an introduction to the learning path and recommendations for transferring knowledge on Microsoft Excel into everyday life).

The study was conducted entirely online. An overview of the study procedure is presented in Figure 4-5. Participants willing to take part in our research could access the study via a link to an online survey, including a pre-questionnaire. In the pre-questionnaire, participants agreed to the privacy and data protection statement and were asked to provide information on their demographics, goal orientations, and task value. Moreover, participants were asked to complete a short knowledge test on Microsoft Excel.

Figure 4-5

Overview of the Study Procedure



Once participants had completed the pre-questionnaire, they were randomly assigned to one of the three experimental conditions and were provided access to the respective (personalized or static) version of the Microsoft Excel learning path, depending on their assigned experimental condition. Participants were given a period of 14 days to complete the learning path. They could log in to the edyoucated-platform and access the learning path as often as they wanted to within the 14-day learning period. Once participants had completed all learning materials of the learning path or the 14-day learning period had passed, they were provided with a link to another online survey, including a post-questionnaire. In the post-questionnaire, participants' satisfaction with their learning process and perceived ease of use of the edyoucated-platform were collected, and participants were again asked to complete a short knowledge test on Microsoft Excel.

The pre- and post-questionnaires were identical across all three conditions. The knowledge tests provided in the pre- and post-questionnaire differed from the assessment questions related to the personalization system within the learning path. The knowledge tests in the pre- and post-questionnaire served to measure participants' knowledge increase during the learning period and did not affect the personalization of the learning path in the two personalized conditions. The pre- and post-questionnaire and the Microsoft Excel learning path were available in German. Sample materials and items were translated into English to present them in this paper.

4.7.2 Participants

Participants were recruited via social media channels, the network of three employer associations, as well as the research team's personal and professional contacts. All adults (i.e., at least 18 years old) interested in completing a Microsoft Excel learning path on the edyoucated-platform could participate in the study. A total number of $N = 328$ participants fully completed the pre-questionnaire. However, $N = 130$ of them did not complete any learning material of the Microsoft Excel learning path and were excluded from the analyses. Further, four participants were excluded due to technical problems. Thus, the sample used for data analyses included a total number of $N = 194$ participants (98 female, 95 male, 1 divers). Participants were between 18 and 75 years old ($M = 40.35$, $SD = 13.05$). Most participants (82%) were working adults. Out of the $N = 194$ participants, 111 started the post-questionnaire, of whom 108 participants fully completed the post-questionnaire. Therefore, analyses including information from the post-questionnaire were based on a sub-sample ranging from 108 to 111 participants.

4.7.3 Measures

Knowledge Increase

Knowledge increase was measured by subtracting the sum of correctly answered questions in the knowledge test of the pre-questionnaire from the sum of correctly answered questions in the knowledge test of the post-questionnaire. Thus, positive values indicated a knowledge increase during the learning period, whereas negative values indicated a knowledge decrease during the learning period. The knowledge test in the pre- and post-questionnaire consisted of eleven single-choice items (e.g., “What happens if you copy a cell with a relative cell reference into another cell in Microsoft Excel?”) related to the content of the Microsoft Excel learning path. The single-choice items were identical in the pre- and the post-questionnaire but presented in a different order.

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. Thus, in the control condition, the sum of completed learning materials was divided by the total number of learning materials related to all 24 skill atoms of the learning path. In the personalized conditions, the sum of completed learning materials was divided by the sum of learning materials related to the skill atoms that had not been identified as mastered by the assessment of the personalization system (i.e., that the participant was not allowed to skip). Learning materials consisted of videos, texts, and short quizzes. Video and text materials were considered completed once participants clicked on the “Complete and continue” button (see Figure 4-1). Quizzes were considered completed once they were answered correctly (participants were prompted to retake quizzes if the quizzes were not answered correctly).

Learner Satisfaction

Learner satisfaction was measured using four items (e.g., “I would recommend the edyoucated-platform to other people”, Cronbach’s $\alpha = .84$) adapted from Paschke et al. (2003). The items were assessed on a 7-point Likert scale (1 = fully disagree, 7 = fully agree).

Goal Orientations

Goal orientations were measured using Spinath et al.’s (2012) questionnaire. Mastery goal orientation was measured using eight items (e.g., “In CE activities, it is important to me to learn as much as possible”, Cronbach’s $\alpha = .80$). Performance-approach goal orientation was assessed using seven items (e.g., “In CE activities, it is important to me that others think that I am clever”, Cronbach’s $\alpha = .88$). Performance-avoidance goal orientation (e.g., “In CE activities, it is important to me that other learners do not think that I am dumb", Cronbach's α = .88) and work-avoidance goal orientation (e.g., "In CE activities, it is important to me to always keep the expenditure of work low", Cronbach's α = .88) were measured with eight items each. All items were assessed on a 7-point Likert scale (1 = fully disagree, 7 = fully agree).

Task Value

Task value was measured using five items (e.g., "I like the subject matter of this course", Cronbach's α = .88) adapted from the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1991, 1993). The items were assessed on a 7-point Likert scale (1 = fully disagree, 7 = fully agree).

Control Variables

We employed participants' *prior knowledge*, measured by the sum of correctly answered questions in the knowledge test of the pre-questionnaire, as a control variable because prior knowledge has been shown to impact motivation and learning outcomes in online learning environments (Kennedy et al., 2015; L.-Y. Li, 2019; Song et al., 2016). Moreover, we controlled for participants' *perceived ease of use* of the edyoucated-platform. Perceived ease of use, which describes the degree to which learners perceive the handling of a learning system as easy and free of effort (Davis, 1986; Granić & Marangunić, 2019; Venkatesh & Davis, 1996), has been considered a key challenge in designing personalized learning environments, as adapting to the diverse characteristics of learners may enhance complexity (Alshammari et al., 2015). Perceived ease of use was measured using five items (e.g., "The edyoucated-platform is easy to use", Cronbach's α = .95) adapted from Sprenger and Schwaninger (2021). The items were assessed on a 7-point Likert scale (1 = fully disagree, 7 = fully agree).

Trace Data for Exploratory Analyses

To investigate exploratorily whether participants' interactions with the personalization system differed depending on the type of prior knowledge assessment (i.e., self-report questions vs. knowledge questions), we calculated the following variables for each participant in the PSRQ and PKQ conditions:

- *Number of skill atoms allowed to skip*: total number of skill atoms that the participant was allowed to skip due to prior knowledge (based on the assessment of the personalization system after possible corrections by the participant)
- *Percentage of corrected skill atoms*: percentage of skill atoms corrected by the participant in the assessment summaries

- *Percentage of unnecessarily completed materials*: portion of opened and completed learning materials from all learning materials that the participant was allowed to skip (based on the assessment of the personalization system after possible corrections by the participant)

4.7.4 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 test Hypotheses 1–3, we conducted multiple linear regression analyses where knowledge increase, learning path completion, and learner satisfaction were regressed on the experimental condition and the control variables (prior knowledge, perceived ease of use). To test Hypothesis 4 and Hypothesis 5, goal orientations and task value, as well as their interactions with the experimental condition, were added to the regression models. In all regression models, continuous predictors were mean-centered for better interpretation of regression results. Simple slope analyses were conducted for significant interaction effects. The regression slopes for three different values of the moderator were explored in the simple slope analyses: weak (representing the 25th percentile of the centered moderator), medium (representing the 50th percentile of the centered moderator), and strong (representing the 75th percentile of the centered moderator). Moreover, we employed *t*-tests for independent samples to investigate exploratorily whether the two personalized conditions differed in the number of skill atoms allowed to skip, the percentage of corrected skill atoms, and the percentage of unnecessarily completed learning materials.

4.8 Results

Descriptive statistics and correlations between variables can be found in Appendix B.

4.8.1 Hypotheses Testing

Effects on Learning Outcomes

Hypothesis 1 postulated that participants' knowledge increase during the learning period should not be lower in the two personalized conditions than in the control condition, although participants in the personalized conditions were allowed to skip learning content. The knowledge increase in the two personalized conditions (PSRQ: $M = 1.38$, $SD = 1.72$; PKQ: $M = 0.78$, $SD = 1.44$) tended to be higher than in the control condition ($M = 0.32$, $SD = 2.21$). As shown in Table 4-1, the regression coefficient for the PSRQ condition was significant, indicating a significantly higher knowledge increase in the PSRQ condition than in the control condition. The regression coefficient for the PKQ condition was not statistically significant. These findings support Hypothesis 1.

According to Hypothesis 2 and Hypothesis 3, participants in the two personalized conditions should be more likely to complete their learning path and more satisfied with their learning process than participants in the control condition. However, contradicting our hypotheses, the experimental condition did not significantly affect learning path completion (see Table 4-2) and learner satisfaction (see Table 4-3).

Table 4-1

Multiple Linear Regression Analysis for Knowledge Increase

Predictor	Regression coefficient					$F(df1, df2)$	p	R^2	$R^2_{adjusted}$
	B	SE	β	t	p				
Model 1 [a]						7.80(4, 103)	< .001	.22	.19
Intercept	0.24	0.36	—	0.67	.503				
Prior knowledge	−0.30	0.06	−.40	−4.63	< .001				
Perceived ease of use	0.19	0.10	.15	1.95	.054				
PSRQ condition	**1.24**	**0.45**	**.32**	**2.75**	**.007**				
PKQ condition	0.72	0.41	.19	1.76	.081				
Model 2						3.26(19, 88)	< .001	.41	.29
Intercept	0.32	0.28	—	1.16	.251				
Prior knowledge	−0.37	0.07	−.49	−4.93	< .001				
Perceived ease of use	0.25	0.11	.20	2.26	.026				
PSRQ condition	**1.30**	**0.39**	**.33**	**3.31**	**.001**				
PKQ condition	0.68	0.37	.18	1.82	.073				
Mastery GO	0.77	0.33	.33	2.37	.020				
Performance-approach GO	−0.70	0.31	−.56	−2.28	.025				
Performance-avoidance GO	1.10	0.29	.79	3.72	< .001				
Work-avoidance GO	−0.26	0.28	−.19	−0.90	.372				
Task value	0.45	0.45	.19	1.01	.317				
PSRQ condition*mastery GO	−0.03	0.62	−.01	−0.05	.965				
PSRQ condition*performance-approach GO	**0.96**	**0.40**	**.41**	**2.42**	**.017**				
PSRQ condition*performance-avoidance GO	**−1.73**	**0.53**	**−.66**	**−3.25**	**.002**				
PSRQ condition*work-avoidance GO	0.73	0.47	.30	1.56	.124				
PSRQ condition*task value	**−1.37**	**0.63**	**−.33**	**−2.17**	**.033**				
PKQ condition*mastery GO	−0.83	0.53	−.19	−1.59	.116				
PKQ condition*performance-approach GO	**1.03**	**0.41**	**.48**	**2.48**	**.015**				
PKQ condition*performance-avoidance GO	**−1.41**	**0.51**	**−.63**	**−2.78**	**.007**				
PKQ condition*work-avoidance GO	−0.01	0.46	−.00	−0.02	.983				
PKQ condition*task value	−0.18	0.57	−.05	−0.31	.755				

Note. N = 108. Continuous predictors were mean-centered. For the experimental condition, dummy variables were created: PSRQ condition (1 = participant was assigned to the PSRQ condition, 0 = participant was not assigned to the PSRQ condition), PKQ condition (1 = participant was assigned to the PKQ condition, 0 = participant was not assigned to the PKQ condition), control condition (1 = participant was assigned to the control condition, 0 = participant was not assigned to the control condition). Since the dummy variable for the control condition was not included in the regression model, the control condition represented the reference category for the experimental condition in the regression model. Significant findings discussed in the text are presented in bold. PSRQ = personalization based on self-report questions, PKQ = personalization based on knowledge questions, GO = goal orientation.

[a] Since homoscedasticity was violated, HC3 correction (Hayes & Cai, 2007) was employed.

Table 4-2

Multiple Linear Regression Analysis for Learning Path Completion

Predictor	Regression coefficient					$F(df1, df2)$	p	R^2	$R^2_{adjusted}$
	B	SE	β	t	p				
Model 1						3.90(4, 105)	.005	.13	.10
Intercept	0.73	0.05	—	14.76	< .001				
Prior knowledge	0.01	0.01	.09	1.01	.314				
Perceived ease of use	0.07	0.02	.32	3.51	.001				
PSRQ condition	0.06	0.07	.09	0.86	.392				
PKQ condition	0.03	0.07	.04	0.39	.698				
Model 2						1.40(19, 90)	.150	.23	.06
Intercept	0.72	0.05	—	13.84	< .001				
Prior knowledge	0.01	0.01	.12	1.06	.293				
Perceived ease of use	0.07	0.02	.32	3.21	.002				
PSRQ condition	0.07	0.07	.10	0.90	.371				
PKQ condition	0.04	0.07	.06	0.56	.574				
Mastery GO	−0.07	0.06	−.18	−1.14	.259				
Performance-approach GO	0.02	0.06	.10	0.35	.728				
Performance-avoidance GO	−0.02	0.06	−.09	−0.37	.709				
Work-avoidance GO	0.03	0.05	.14	0.59	.560				
Task value	0.01	0.09	.04	0.17	.866				
PSRQ condition*mastery GO	0.18	0.12	.22	1.55	.125				
PSRQ condition*performance-approach GO	−0.01	0.07	−.01	−0.07	.946				
PSRQ condition*performance-avoidance GO	0.11	0.10	.26	1.15	.253				
PSRQ condition*work-avoidance GO	−0.06	0.09	−.16	−0.74	.463				
PSRQ condition*task value	−0.17	0.12	−.25	−1.42	.160				
PKQ condition*mastery GO	0.04	0.10	.05	0.37	.714				
PKQ condition*performance-approach GO	0.05	0.08	.13	0.60	.549				
PKQ condition*performance-avoidance GO	0.00	0.10	.01	0.02	.984				
PKQ condition*work-avoidance GO	−0.09	0.09	−.21	−0.98	.329				
PKQ condition*task value	−0.02	0.11	−.03	−0.21	.836				

Note. $N = 110$. Continuous predictors were mean-centered. For the experimental condition, dummy variables were created: PSRQ condition (1 = participant was assigned to the PSRQ condition, 0 = participant was not assigned to the PSRQ condition), PKQ condition (1 = participant was assigned to the PKQ condition, 0 = participant was not assigned to the PKQ condition), control condition (1 = participant was assigned to the control condition, 0 = participant was not assigned to the control condition). Since the dummy variable for the control condition was not included in the regression model, the control condition represented the reference category for the experimental condition in the regression model. PSRQ = personalization based on self-report questions, PKQ = personalization based on knowledge questions, GO = goal orientation.

Table 4-3

Multiple Linear Regression Analysis for Learner Satisfaction

Predictor	Regression coefficient					$F(df1, df2)$	p	R^2	$R^2_{adjusted}$
	B	SE	β	t	p				
Model 1						6.32(4, 105)	< .001	.19	.16
Intercept	4.82	0.25	—	19.58	< .001				
Prior knowledge	−0.00	0.06	−.01	−0.06	.953				
Perceived ease of use	0.46	0.10	.43	4.81	< .001				
PSRQ condition	−0.38	0.35	−.11	−1.15	.272				
PKQ condition	0.16	0.34	.05	0.46	.646				
Model 2						2.15(19, 90)	.009	.31	.17
Intercept	4.78	0.25	—	18.91	< .001				
Prior knowledge	−0.01	0.07	−.02	−0.19	.846				
Perceived ease of use	0.41	0.10	.38	3.98	< .001				
PSRQ condition	−0.34	0.36	−.10	−0.94	.350				
PKQ condition	0.17	0.34	.05	0.50	.617				
Mastery GO	−0.61	0.30	−.30	−2.05	.044				
Performance-approach GO	0.30	0.28	.28	1.08	.283				
Performance-avoidance GO	0.01	0.27	.01	0.03	.974				
Work-avoidance GO	−0.15	0.27	−.12	−0.56	.579				
Task value	0.65	0.42	.32	1.57	.119				
PSRQ condition*mastery GO	**1.16**	**0.58**	**.27**	**2.03**	**.046**				
PSRQ condition*performance-approach GO	−0.02	0.36	−.01	−0.06	.949				
PSRQ condition*performance-avoidance GO	−0.11	0.49	−.05	−0.23	.816				
PSRQ condition*work-avoidance GO	0.26	0.43	.12	0.60	.548				
PSRQ condition*task value	−0.73	0.59	−.20	−1.24	.217				
PKQ condition*mastery GO	**1.11**	**0.49**	**.30**	**2.28**	**.025**				
PKQ condition*performance-approach GO	−0.42	0.38	−.23	−1.11	.270				
PKQ condition*performance-avoidance GO	0.29	0.47	.15	0.62	.538				
PKQ condition*work-avoidance GO	−0.18	0.43	−.08	−0.42	.675				
PKQ condition*task value	−0.80	0.54	−.23	−1.49	.139				

Note. N = 110. Continuous predictors were mean-centered. For the experimental condition, dummy variables were created: PSRQ condition (1 = participant was assigned to the PSRQ condition, 0 = participant was not assigned to the PSRQ condition), PKQ condition (1 = participant was assigned to the PKQ condition, 0 = participant was not assigned to the PKQ condition), control condition (1 = participant was assigned to the control condition, 0 = participant was not assigned to the control condition). Since the dummy variable for the control condition was not included in the regression model, the control condition represented the reference category for the experimental condition in the regression model. Significant findings discussed in the text are presented in bold. PSRQ = personalization based on self-report questions, PKQ = personalization based on knowledge questions, GO = goal orientation.

The Moderating Role of Motivational Dispositions

Hypothesis 4 postulated that participants' goal orientations should moderate the effects of the experimental condition on (a) knowledge increase, (b) learning path completion, and (c) learner satisfaction. Supporting Hypothesis 4a, significant interaction effects between the experimental condition and performance-approach goal orientation as well as performance-avoidance goal orientation on knowledge increase were found (see Table 4-1). The simple slope analyses of the interaction effects are visualized in Figure 4-6. The slopes for the experimental condition increased with participants' performance-approach goal orientation. The knowledge increase for participants with a strong performance-approach goal orientation was significantly higher in the personalized conditions compared to the control condition, whereas the effects were attenuated for participants with a medium and weak performance-approach orientation. The knowledge increase for participants with a weak performance-approach goal orientation even tended to be slightly lower in the PKQ condition compared to the control condition, but the negative slope was not statistically significant.

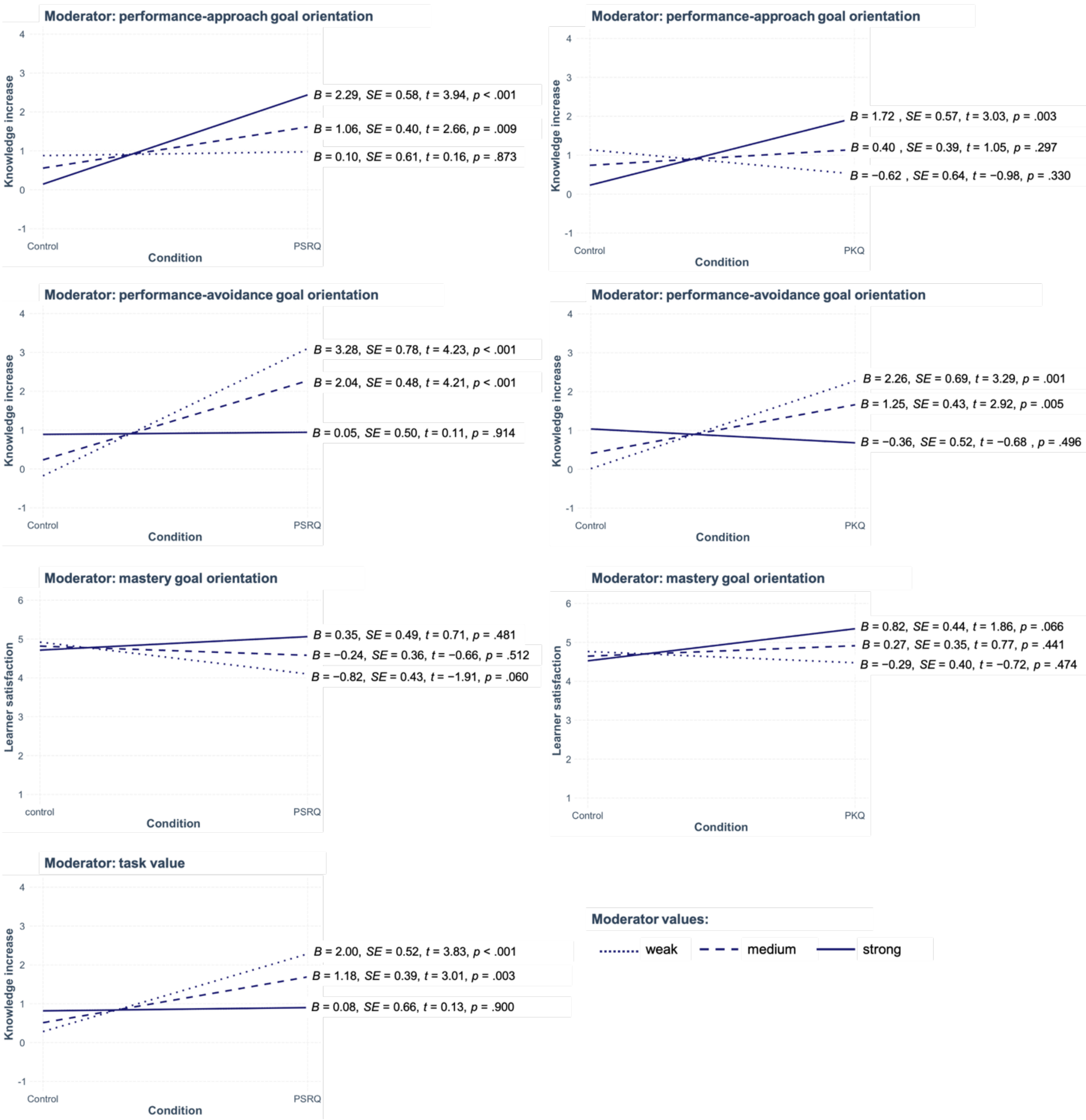
The interaction effects for performance-avoidance goal orientation pointed in the opposite direction (see Figure 4-6): The slopes for the experimental condition decreased as performance-avoidance goal orientation increased. For participants with a weak and medium performance-avoidance goal orientation, the knowledge increase was significantly higher in the personalized conditions than in the control condition, whereas the knowledge increase for participants with a strong performance-avoidance goal orientation did not differ between the personalized conditions and the control condition. The slope for the PKQ condition for learners with a strong performance-avoidance goal orientation tended to be slightly negative, indicating a slightly lower knowledge increase in the PKQ condition than in the control condition, but this difference was not significant.

No significant interaction effects between the experimental condition and mastery goal orientation and work-avoidance goal orientation on knowledge increase were detected (see Table 4-1). Moreover, contradicting Hypothesis 4b, the interaction effects between the experimental condition and goal orientations on learning path completion were not significant (see Table 4-2).

Supporting Hypothesis 4c, significant interaction effects between the experimental condition and mastery goal orientation on learner satisfaction were found (see Table 4-3). As shown in Figure 4-6, the slopes for the experimental condition increased with participants' mastery goal orientation. Participants with a strong mastery goal orientation tended to be more satisfied in the personalized conditions than in the control condition, whereas the effects were attenuated or slightly reversed for participants with a medium and weak mastery goal orientation. However, none of the slopes for the selected three values of mastery goal orientation significantly differed from zero. No significant interaction effects between the experimental condition and performance-approach, performance-avoidance, and work-avoidance goal orientation on learner satisfaction were found. Thus, our findings partially support Hypothesis 4.

Figure 4-6

Simple Slope Analyses for Significant Interaction Effects



Note. Moderators were mean-centered. Performance-approach goal orientation: weak (25th percentile) = −1.17, medium (50th percentile) = −0.17, strong (75th percentile) = 1.11. Performance-avoidance goal orientation: weak (25th percentile) = −1.09, medium (50th percentile) = −0.37, strong (75th percentile) = 0.77. Mastery goal orientation: weak (25th percentile) = −0.43, medium (50th percentile) = 0.07, strong (75th percentile) = 0.57. Task value: weak (25th percentile) = −0.54, medium (50th percentile) = 0.06, strong (75th percentile) = 0.86. PSRQ = personalized condition based on self-report questions, PKQ = personalization based on knowledge questions.

Hypothesis 5 postulated that participants' task value should moderate the effects of the experimental condition on (a) knowledge increase, (b) learning path completion, and (c) learner satisfaction. Supporting Hypothesis 5a, the interaction effect between the PSRQ condition and task value on knowledge increase was significant (see Table 4-1). As shown in Figure 4-6, the slopes for the PSRQ condition increased as task value decreased. For participants with a weak and medium task value, the knowledge increase was significantly higher in the PSRQ condition than in the control condition, whereas the effect of the PSRQ condition on knowledge increase was not significant for participants with a strong task value. The interaction effect between the PKQ condition and task value on knowledge increase was not significant (see Table 4-1). Moreover, contradicting Hypothesis 5b and Hypothesis 5c, no significant interaction effects between the experimental condition and task value on learning path completion (see Table 4-2) and learner satisfaction (see Table 4-3) were found. Thus, our findings partially support Hypothesis 5.

4.8.2 Exploratory Analyses

Participants in the PSRQ condition (M = 6.22, SD = 6.43) were allowed to skip significantly fewer skill atoms than participants in the PKQ condition (M = 8.32, SD = 5.51), $t(132) = -2.03$, $p = .045$, $d = -0.35$. In both personalized conditions, participants corrected only a small portion of skill atoms in the assessment summaries. There was no statistically significant difference in the percentage of corrected assessments between the PSRQ (M = 0.02, SD = 0.10) and the PKQ (M = 0.02, SD = 0.07) condition, $t(128) = -0.30$, $p = .762$, $d = -0.05$. However, there was a statistically significant difference in the percentage of unnecessarily completed materials between the two personalized conditions. Participants in the PSRQ condition (M = 0.05, SD = 0.19) completed significantly fewer learning materials that they were allowed to skip than learners in the PKQ condition (M = 0.29, SD = 0.18), $t(118) = -7.33$, $p < .001$, $d = -1.34$.

4.9 Discussion

This study investigated the effects of TEPLEs-PK that allow learners to skip learning content based on their individual levels of prior knowledge on learning outcomes in CE, as well as how learners' motivational dispositions moderate these effects. According to our findings, TEPLEs-PK may positively affect knowledge increase in CE (Hypothesis 1). However, no main effects of TEPLEs-PK on learning path completion (Hypothesis 2) and learner satisfaction (Hypothesis 3) were found. Learners' goal orientations (Hypothesis 4) and task value (Hypothesis 5) moderated the effects of TEPLEs-PK on knowledge increase and learner satisfaction.

4.9.1 Interpretation of Results and Theoretical Implications

Effect on Knowledge Increase and the Role of Motivational Dispositions

Consistent with previous research focusing on TEPLEs-PK in higher education (Arsovic & Stefanovic, 2020; Niknam & Thulasiraman, 2020), our findings suggest that TEPLEs-PK may help learners acquire new knowledge. By allowing learners to skip learning content based on their prior knowledge, TEPLEs-PK may prevent learners from inefficiently using their time on learning content they have already mastered and help them save time to focus on unmastered content to learn something new (Alshammari & Qtaish, 2019; Rasch & Middelbeck, 2022). Since lack of time has been considered a key challenge for learners in CE (Eriksson et al., 2017; Schröer et al., 2022; W. Wang et al., 2023), TEPLEs-PK that help learners save learning time can be a useful tool for supporting learning processes in CE.

However, the findings of our study also show that not every learner benefits from TEPLEs-PK equally, as performance-approach and performance-avoidance goal orientation, as well as task value, moderated the effects of TEPLEs-PK on knowledge increase. We expected that the stronger learners' performance-approach goal orientation, the less they should benefit from TEPLEs-PK that allow them to skip already mastered learning content, as learners with a strong performance-approach goal orientation want to demonstrate their knowledge, skills, and competences (Basavaraj & Garibay, 2018; Senko et al., 2011; Spinath et al., 2012). However, contrary to our expectations, our findings indicate that the stronger the learners' performance-approach goal orientation, the more they benefit from TEPLEs-PK in terms of knowledge increase. Possibly, learners with a strong performance-approach goal orientation might have seen the assessment questions in the personalized conditions as an opportunity to demonstrate their knowledge, skills, and competences and, therefore, benefited more from the personalization system than learners with a weak performance-approach goal orientation. These findings are consistent with Duffy and Azevedo's (2015) and Lallé et al.'s (2016) studies, in which especially learners with a strong performance-approach goal orientation benefited from personalized feedback and prompts in higher education. Moreover, our findings are consistent with Schumacher and Ifenthaler's (2018) study that revealed a positive relationship between learners' performance-approach goal orientation and perceived support from learning analytics in higher education.

Consistent with our expectations, the findings of our study indicate that the stronger the learners' performance-avoidance goal orientation, the less they benefit from TEPLEs-PK in terms of knowledge increase. Learners with a strong performance-avoidance goal orientation are afraid of showing their incompetence (Elliot, 1999; Senko et al., 2011). Therefore, they might prefer to focus on learning content they have already mastered and might feel uncomfortable if this learning content is skipped from the learning path. Moreover, learners with a strong performance-avoidance goal orientation might have seen the assessment questions of the personalization system as a potential risk of getting negative judgments about their knowledge, skills, and competences (Basavaraj & Garibay, 2018; Kaplan & Maehr, 2007; Spinath et al., 2012).

No significant interaction effects between the experimental condition and mastery and work-avoidance goal orientation on knowledge increase were detected in our study. Although researchers have suggested that mastery and work-avoidance goal orientation may impact achievement-related behaviors and preferences (Spinath & Schöne, 2019; Urdan & Kaplan, 2020; Wolters, 2004), we conclude that mastery and work-avoidance goal orientation do not impact the effects of TEPLEs-PK on knowledge increase in CE.

In our study, the positive effect of the PSRQ condition (compared to the control condition) on knowledge increase decreased as participants' task value increased. Task value positively correlates with learner engagement (Shang et al., 2023; Vo & Ho, 2024), effort (Dietrich et al., 2017; F. Wu et al., 2020), and persistence (Shang et al., 2023). Therefore, learners with a strong task value may be motivated to spend time on learning materials and may consider skipping learning content less important than learners with a weak task value. Moreover, the personalization system of the edyoucated-platform might have helped learners with a weak task value save their effort and motivation for learning content they still need to learn in order to increase their knowledge rather than wasting effort and motivation on learning content they have already mastered (Alshammari & Qtaish, 2019; Rasch & Middelbeck, 2022). However, in our study, the interaction effect between the PKQ condition and task value on knowledge increase was not significant. We conclude that learners' task value is more relevant to the effects of TEPLEs-PK if learners can self-report their prior knowledge than if prior knowledge is assessed using knowledge questions. When self-reporting their prior knowledge, learners may have more control over the personalization system and may influence the personalization system more easily based on their task value beliefs than if they have to answer knowledge questions (Van de Mortel, 2008; Vinski & Watter, 2012).

Effect on Learning Path Completion and the Role of Motivational Dispositions

Our findings rebut the assumptions of researchers who have proposed TEPLEs-PK as a means for reducing dropout rates in CE (Al-Chalabi et al., 2021; Rasch & Middelbeck, 2022; Smaili et al., 2022, 2023). Although, on average, participants in the two personalized conditions were allowed to skip 7.24 skill atoms, the experimental condition did not affect learning path completion. Moreover, no interaction effects between the experimental condition and learners' motivational dispositions on learning path completion were found.

Nevertheless, our findings are consistent with some previous experimental studies. For example, in Niknam and Thulasiraman's (2020) study, TEPLEs-PK did not affect course completion time in higher education. Moreover, Rosen et al.'s (2018) personalized learning system, tailoring learning activities to individual learners' performance when interacting with learning content in a MOOC, did not affect course completion. The dropout rate in our study was high. Only around 15% of the participants completed their learning path, which is comparable to the dropout rates of MOOCs (Chi et al., 2023; Dass et al., 2021; Rosen et al., 2018). Our findings suggest that, independent of learners' motivational dispositions, TEPLEs-PK are not sufficient to reduce the high dropout rates associated with online CE. Additional support (e.g., support of self-regulated learning [SRL] strategies) might be needed to enhance learners' motivation to continue and complete CE activities (Psathas et al., 2023; Teich et al., 2024).

Effect on Learner Satisfaction and the Role of Motivational Dispositions

Inconsistent with previous research suggesting that learners appreciate personalized learning environments (Alamri et al., 2020; Fromm & Ifenthaler, 2024; Xu et al., 2024), our study did not detect a main effect of the experimental condition on learner satisfaction. Our findings indicate that the relationship between TEPLEs-PK and learner satisfaction depends on learners' mastery goal orientation. The stronger the learners' mastery goal orientation, the more they appreciate TEPLEs-PK that allow them to skip learning content. Learners with a strong mastery goal orientation focus on personal growth and development (Elliot, 1999; Kaplan & Maehr, 2007; Spinath et al., 2012; Wolters, 2004). Therefore, they may appreciate TEPLEs-PK, which help them learn something new by focusing on learning content they have not yet mastered, whereas TEPLEs-PK are less relevant for learners with a weak mastery goal orientation (Basavaraj & Garibay, 2018; Schumacher & Ifenthaler, 2018).

In our study, no interaction effects between the experimental condition and performance-approach, performance-avoidance, and work-avoidance goal orientation on learner satisfaction were detected. We conclude that performance-approach and performance-avoidance goal orientations play a more important role for the effects of TEPLEs-PK on knowledge increase, while mastery goal orientation is more relevant to the effects of TEPLEs-PK on learner satisfaction. Learners with a strong performance-approach or performance-avoidance goal orientation focus on interpersonal criteria for defining success, while learners with a strong mastery goal orientation define success based on intrapersonal rather than interpersonal criteria (Elliot, 1999; Senko et al., 2011). Therefore, performance goal orientation might be more relevant to the explanation of objective learning outcomes, such as knowledge increase, whereas mastery goal orientation might play a more important role in explaining subjective learning outcomes, such as learner satisfaction (Juhaňák et al., 2023). Contrary to our expectations, work-avoidance goal orientation moderated the effects of TEPLEs-PK neither on knowledge increase nor on learner satisfaction. Although learners with a strong work-avoidance goal orientation want to keep the expenditure of work and effort as minimal as possible (King & McInerney, 2014; Spinath & Schöne, 2019; Spinath et al., 2012), they do not benefit from TEPLEs-PK that allow them to skip learning content. These findings are consistent with Schumacher and Ifenthaler's (2018) study, in which work-avoidance goal orientation was not related to learners' perceived support from learning analytics in higher education. We conclude that work-avoidance goal orientation plays a minor role for the effectiveness of TEPLEs-PK in supporting learning processes in CE.

Moreover, contrary to our expectations, task value did not moderate the effect of TEPLEs-PK on learner satisfaction. Further, no main effect of task value on learner satisfaction could be detected in our study, which is inconsistent with previous research (e.g., Kok et al., 2024; Yalçın & Dennen, 2024; Zhang et al., 2024). We suggest that methodological issues might have caused the insignificant (interaction) effects of task value on learner satisfaction. On average, participants in our study reported high task value scores with a rather low standard deviation (M = 6.14, SD = 0.84 on a 7-point Likert scale). Possibly, there was not enough variance of task value in our sample to detect significant (interaction) effects on learner satisfaction.

Personalization Based on Self-Report Questions vs. Knowledge Questions

According to our exploratory analyses, participants in the PSRQ condition were allowed to skip fewer skill atoms than learners in the PKQ condition and completed fewer learning materials that they were allowed to skip. These findings indicate that participants in the PSRQ condition were reluctant in reporting their prior knowledge and did not overestimate their prior knowledge. This interpretation is also supported by the slightly higher knowledge increase in the PSRQ condition than in the PKQ condition.

Our findings complement previous research criticizing self-report questionnaires for being subject to subjective biases, such as social desirability (Lavidas et al., 2022; Snibsøer et al., 2018; Van de Mortel, 2008). Our findings suggest that self-report questions can be a useful tool to assess prior knowledge in TEPLEs-PK. In comparison to knowledge questions, self-report questions to assess learners' prior knowledge are rather easy to create and administer

(Snibsøer et al., 2018). Although skill atoms on the edyoucated-platform are considered to be small units of learning artifacts, it is a challenging task to create a single knowledge question that covers all the content of a skill atom, and more than one knowledge question might be necessary to assess learners' prior knowledge of a skill atom validly. This might be the reason why learners in the PKQ condition completed more learning materials that they were allowed to skip than learners in the PSRQ condition. Possibly, the assessment of prior knowledge was less accurate in the PKQ condition than in the PSRQ condition, and participants wanted to process the learning materials that they were actually allowed to skip. Nevertheless, in both conditions, the participants corrected only a very small percentage of atomic skills in the assessment summaries. These findings indicate that learners trust in assessing their prior knowledge through self-report and knowledge questions.

4.9.2 Practical Implications

Our study provides empirical evidence for the effectiveness of TEPLEs-PK in supporting learning processes in CE and may help researchers, system designers, and CE specialists develop and implement effective TEPLEs-PK for CE. Since our findings indicate that depending on their motivational dispositions, learners may benefit differently from TEPLEs-PK, personalized learning environments that solely consider learners' prior knowledge may not be sufficient to meet the diverse needs of learners in CE. More personalized approaches that consider learners' motivational dispositions are needed for CE (Duffy & Azevedo, 2015; Lallé et al., 2016; Schumacher & Ifenthaler, 2018). For example, TEPLEs-PK could measure learners' goal orientations and task value when they start a new learning path and adapt the personalization system accordingly: In the case of a strong mastery or performance-approach goal orientation, the system may skip learning content based on learners' prior knowledge, as implemented on the edyoucated-platform. In the case of a strong performance-avoidance goal orientation or task value, the system may alternate between already mastered and unmastered learning content.

Moreover, our study provides empirical support for the use of self-report questions to assess learners' prior knowledge in TEPLEs-PK. Although self-report questions have been criticized for being subject to subjective biases (Lavidas et al., 2022; Snibsøer et al., 2018; Van de Mortel, 2008), our study suggests that self-report questions may measure learners' prior knowledge in CE more accurately and efficiently than knowledge questions if only a limited number of assessment questions can be asked.

4.9.3 Limitations and Future Research

Our study is subject to limitations that may provide implications for future research. First, since our study took place entirely online, we have no control over how deeply participants engaged in the learning materials on the edyoucated-platform. For example, participants might have completed learning materials by simply clicking on the "Complete and continue" button, but without processing the materials. Thus, the measurement of learning path completion might have been biased in our study. Therefore, future research should evaluate the effects of TEPLEs-PK on learning outcomes in CE in a more controlled setting.

Second, since participation in our study and the CE activity on the edyoucated-platform were voluntary, predominantly learners motivated for CE and interested in Microsoft Excel might have decided to participate in our study. However, in CE practice, participation in CE activities is not always voluntary but may also be regulated by external entities, such as employers (Hemmler et al., 2023). Therefore, the distribution of motivational dispositions in our study might not be representative of all types of CE activities, and future research should investigate TEPLEs-PK in the context of mandatory CE activities (e.g., in business organizations).

Third, our study considered only one learning path (Microsoft Excel) of the edyoucated-platform. Thus, the generalizability of our findings to learning paths and topics other than Microsoft Excel is limited. Future research should investigate the effects of TEPLEs-PK on learning outcomes for a broader range of learning paths.

Fourth, only learners' goal orientations and task value were considered as moderators. Further motivational dispositions such as self-efficacy or self-concept might influence learners' perceptions of and interactions with personalized learning support (Aguilar, 2023; Schumacher & Ifenthaler, 2018). Thus, future research should focus on further motivational dispositions that may moderate the effects of TEPLEs-PK on learning outcomes in CE.

4.9.4 Conclusion

TEPLEs-PK aim at supporting learning processes by tailoring learning activities to the individual learner's prior knowledge (Chaipidech et al., 2022; Xue-jun et al., 2021). In the present study, the effects of TEPLEs-PK on learning outcomes in CE were investigated. Our findings suggest that TEPLEs-PK may positively affect knowledge increase. However, our findings also indicate that the benefits of TEPLEs-PK in CE may depend on learners' goal orientations and task value. Our study provides a sound basis for implementing TEPLEs-PK in CE. Future research should investigate the effects of TEPLEs-PK on different types of CE and different learning paths, as well as identify additional motivational dispositions that may moderate the effects of TEPLEs-PK on learning outcomes in CE.

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5. Paper 3: Self-Regulated Learning Strategies in Continuing Education: A Systematic Review and Meta-Analysis

5.1 Introduction

Due to rapid social and technological changes in today's (working) world, continuing education (CE) is becoming increasingly important. Individuals are constantly required to participate in CE activities and to acquire new knowledge, skills, and competences to successfully adapt to these changes (Cuyvers et al., 2021; Kittel et al., 2021; Manuti et al., 2015). CE is usually characterized by high learner autonomy and requires learners to engage in self-regulated learning (SRL) processes (Nawrot & Doucet, 2014; Sitzmann & Ely, 2011). SRL describes active and dynamic processes whereby learners monitor and control their own cognitions, affects, and behaviors to achieve personal learning goals (Pintrich, 2000; Zimmerman & Schunk, 2011). When engaging in SRL, learners use various strategies to optimize their learning process and to achieve their goals. These SRL strategies include cognitive (e.g., rehearsal, elaboration), metacognitive (e.g., planning, monitoring), and resource management (e.g., time management, help seeking) strategies (Pintrich et al., 1991, 1993).

SRL strategies have been considered key competences for CE and have been linked to learning performance in empirical studies (Chaker & Impedovo, 2021; Haemer et al., 2017). However, the nature of SRL in CE still remains unclear, as comprehensive systematic reviews and meta-analyses investigating the factors triggering and inhibiting learners' use of SRL strategies, as well as the effects of SRL strategies in CE, are scarce. Systematic reviews on SRL in CE have primarily focused on Massive Open Online Courses (MOOCs) and summarized SRL theories (e.g., Alonso-Mencía et al., 2020), SRL strategies (e.g., Lee et al., 2019), SRL measurement instruments (e.g., Cerón et al., 2020), and SRL interventions (e.g., Lee et al., 2019) studied in the context of MOOCs. A comprehensive systematic review investigating potential antecedents and outcomes of SRL strategies in CE and focusing on other types of CE than MOOCs is lacking. CE can occur through different types of learning activities (e.g., online vs. face-to-face, work-related vs. non-work-related, formal vs. informal learning activities), which differ in their nature of learning and, therefore, might impact SRL (Beishuizen & Steffens, 2011; Schiersmann, 2007; Tynjälä, 2008, 2013).

Moreover, meta-analyses quantifying the strength of the relationships between SRL strategies and potential antecedents and outcomes in CE are scarce. While SRL strategies have been extensively researched in meta-analyses focusing on K-12 (e.g., Dent & Koenka, 2016; J. Li et al., 2018) and higher education (e.g., Broadbent & Poon, 2015; Theobald, 2021), Sitzmann and Ely's (2011) meta-analysis is the only meta-analysis on SRL strategies that included studies focusing on CE. Sitzmann and Ely (2011) found positive relationships between several SRL strategies and achievement motivation as well as learning performance. However, they did not investigate the relationships between SRL strategies and other factors that may be associated with SRL strategies in CE (e.g., learner satisfaction, job demands; K. Li, 2019; Raemdonck et al., 2014). Moreover, Sitzmann and Ely's (2011) meta-analysis did not focus on CE exclusively, and the majority of the included studies (82%) focused on higher education. Thus, the informative value for CE is limited, as CE differs from higher education in several aspects (e.g., the relevance of informal learning activities, learners' professional situation), which might impact SRL (Eriksson et al., 2017; Kittel et al., 2021; Knowles et al., 2012). Further, only work-related, formal CE was considered, excluding all types of non-work-related and informal learning activities (Sitzmann & Ely, 2011).

Accordingly, a comprehensive systematic review and meta-analysis investigating factors associated with SRL strategies in CE is expected to help reveal the nature of SRL in CE and identify the most important SRL strategies for different types of CE. Such insights may help understand how learners can best apply SRL strategies, identify conditions that require SRL support, and design interventions to support SRL in CE (Broadbent & Poon, 2015; Tang, 2021). Therefore, our systematic review and meta-analysis aim to identify factors associated with learners' use of SRL strategies in CE as well as investigate the strength and potential moderators of the underlying relationships.

5.2 Continuing Education

CE is a broad term that encompasses all learning activities that are distinct from professional apprenticeships, K-12, and higher education (Demary et al., 2013; *Further and Higher Education Act*, 1992). CE aims to develop or renew knowledge (i.e., cognitive representations of learning content; Carter, 1985; Winterton et al., 2005), skills (i.e., abilities to perform a specific task; Attewell, 1990; Carter, 1985), and competences (i.e., knowledge, skills, behaviors, and attitudes necessary to be successful in a job or particular area; Le Deist & Winterton, 2005) after the completion of an initial phase of education (Demary et al., 2013; Schiersmann, 2007). Higher education institutions are increasingly involved in the design of CE activities by offering MOOCs or professional certificate programs (Agyepong & Okyere, 2018; Wulf et al., 2014), which differ from traditional higher education in that they do not lead to an undergraduate or consecutive graduate degree and have either no or special admission regulations (Heidelberg University, 2023; Versuti et al., 2020; Wulf et al., 2014).

CE can be work-related or non-work-related (Demary et al., 2013; *Further and Higher Education Act*, 1992). Learners engaging in work-related CE aim at developing or renewing knowledge, skills, and competences that are relevant to their job position. Work-related CE may (but does not have to be) financially supported by the employer and be accounted as part of the work (Kyndt & Baert, 2013; Schiersmann, 2007). In contrast, non-work-related CE focuses on knowledge, skills, and competences that are not directly linked to a specific job position (Demary et al., 2013; Schiersmann, 2007). Both work-related and non-work-related CE can occur through formal, non-formal, and informal learning activities. Formal CE refers to organized learning activities that are regulated by law and may lead to a state-approved certificate (Misko, 2008; Schumacher, 2018). Non-formal CE comprises all other forms of organized CE activities that are not regulated by law (Radcliffe & Colletta, 1989; Schumacher, 2018). Informal CE refers to unorganized and sometimes unconscious and unintended learning activities that occur through experiences in daily (work) life (Eraut, 2004; Schiersmann, 2007; Schumacher, 2018).

5.3 Self-Regulated Learning and Self-Regulated Learning Strategies

According to SRL theories, learners are active participants in their own learning process and potentially able to monitor and control certain aspects of their learning (Pintrich, 2000; Zimmerman & Schunk, 2011). Several authors have suggested that SRL consists of at least three cyclical phases. First, in the *forethought phase*, learners analyze the learning task, set learning goals, and build a plan to approach these goals. Second, in the *performance phase*, learners carry out the plan they created beforehand as well as monitor and control their learning progress. Third, in the *self-reflection phase*, learners evaluate their overall learning performance in relation to their learning goals. This evaluation may lead them to adapt their strategies for future learning sessions and may influence subsequent forethought phases (Panadero, 2017; Pintrich, 2000; Winne & Hadwin, 1998; Zimmerman, 2000).

All learners self-regulate their learning process to some degree (Winne, 2011, 2022). However, good self-regulators are distinguished by their effective use of SRL strategies (Pintrich et al., 1993; Zimmerman, 1990). SRL strategies have been conceptualized differently across SRL theories, but they can broadly be classified into cognitive, metacognitive, and resource management strategies (Pintrich et al., 1993; Theobald, 2021). *Cognitive strategies* facilitate the processing of information from learning materials (Pintrich et al., 1991, 1993;

Wild & Schiefele, 1994; Winne, 2011). *Metacognitive strategies* describe second-order cognitions that help learners monitor and control their cognition and application of cognitive strategies. Metacognitive strategies involve goal setting and planning as well as monitoring, evaluating, and adjusting one's learning behavior. *Resource management strategies* summarize strategies for regulating other internal and external resources (e.g., time, effort) besides cognition (Pintrich, 1999; Pintrich et al., 1991, 1993; Theobald, 2021; Wild & Schiefele, 1994). Table 5-1 provides an overview of different SRL strategies identified in previous literature and studied in the present systematic review and meta-analysis.

Previous systematic reviews and meta-analyses have identified potential antecedents and outcomes of SRL in K-12 (e.g., Dent & Koenka, 2016; Fong et al., 2021; J. Li et al., 2018) and higher education (e.g., Broadbent & Poon, 2015; Panadero et al., 2017; Zheng et al., 2023). For example, individual (e.g., reflective skills, emotions; van Houten-Schat et al., 2018; Zheng et al., 2023) and contextual (e.g., course characteristics, social support; Martínez-López et al., 2023; Panadero et al., 2017) factors have been associated with SRL strategies in K-12 and higher education. Moreover, several meta-analyses have found positive associations between SRL strategies and learning performance in K-12 (e.g., J. Li et al., 2018) and higher education (e.g., Broadbent & Poon, 2015).

Table 5-1

Coded Variables and Intercoder Reliability

Variable	Codes	Description	Krippendorff's alpha
SRL strategies	**Cognitive strategies**		.78
	Rehearsal	Repeating learning content over and over again to memorize information (Pintrich et al., 1991, 1993)	
	Elaboration	Connecting information from different sources and integrating information into existing knowledge structures (e.g., paraphrasing, creating analogies; Pintrich et al., 1991, 1993; Wild & Schiefele, 1994)	
	Organization	Transforming learning content into a new structure that is easier to process (e.g., outlining, clustering; Pintrich et al., 1991, 1993; Wild & Schiefele, 1994)	
	Critical thinking	Applying learning content to new situations or making critical judgements (Pintrich et al., 1991, 1993)	
	Other	Other measures of cognitive strategies (e.g., task strategies, analytical strategies; Vanslambrouck, Zhu, Pynoo, Lombaerts, et al., 2019; Warr & Bunce, 1995)	

Variable	Codes	Description	Krippendorff's alpha
	Metacognitive strategies		
	Goal setting and planning	Thinking about what needs to be learned, setting learning goals, and building a plan (e.g., a study schedule) to approach these goals (Theobald, 2021; Zimmerman & Pons, 1986)	
	Self-monitoring	Self-observing the current learning progress, knowledge, or comprehension of the learning content (Theobald, 2021)	
	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 (Pintrich et al., 1991, 1993; Theobald, 2021)	
	Self-satisfaction	Recognizing the intrinsic value of the current learning activity (e.g., its relation to long-term goals or personal interests; Fontana et al., 2015)	
	Metacognitive self-regulation	Composite score of metacognitive strategies, including planning, monitoring, and regulating learning processes (Pintrich et al., 1991, 1993)	
	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 (Pintrich et al., 1991, 1993)	
	Effort regulation	Controlling motivation and effort to persist even when faced with difficulties, distractions, or uninteresting tasks (Pintrich et al., 1991, 1993)	
	Help seeking	Seeking assistance from instructors, peers, or other resources when needed (Pintrich et al., 1991, 1993)	
	Peer learning	Communicating and collaborating with peers (e.g., in a study group; Pintrich et al., 1991, 1993)	
	Other	Other measures of resource management strategies (e.g., self-management, practical application; Agonács et al., 2020; Warr et al., 1999)	
Factors associated with SRL strategies	**Learning process-related factors**		.72
	Achievement motivation	An individual's desire to perform well on a task for which standards of excellence exist (Brunstein & Heckhausen, 2018); a product of individuals' expectancy of how well they will perform the task and the value they attribute to the task (Eccles, 1983; Eccles & Wigfield, 2020, 2023; Wigfield, 1994; Wigfield & Eccles, 2000)	
	Learning performance	Knowledge, skills, or competences acquired through educational activities (e.g., grades, test scores, self-reported competences; Chaker & Impedovo, 2021; Wan et al., 2012)	
	Learner engagement	Learners' cognitive, behavioral, and affective involvement in learning activities (Halverson & Graham, 2019; Kizilcec et al., 2017; Schunk & Mullen, 2012)	
	Learner satisfaction	Positive affects and perceived contentment related to participation in CE; learners who are satisfied with a CE activity would recommend the activity to friends and engage in a similar activity again (Martin & Bolliger, 2022; Wan et al., 2012; Wu et al., 2015)	

Variable	Codes	Description	Krippendorff's alpha
	Completion of the CE activity	Completion of the CE activity (vs. dropout; Moreno-Marcos et al., 2020)	
	Lack of time available for learning	Limitation of the time the learner can spend on the CE activity due to professional and family commitments (Hemmler & Ifenthaler, 2022; Milligan & Littlejohn, 2016)	
	Avoidance behavior	Motivation to avoid negative outcomes as well as motivation to avoid work and effort (Elliot et al., 2006; Spinath et al., 2012)	
	Individual goal achievement	Achievement of individually set learning goals (Kizilcec et al., 2017)	
	Learner-related factors		
	Age	Learner's age	
	Educational level	Learner's educational level	
	Gender	Learner's gender	
	Prior knowledge	Prior experiences with the course topic (Peters-Burton & Botov, 2017; Winne, 1996)	
	CE experience	Learner's previous participation in CE activities (e.g., number of previous CE activities completed; Kizilcec et al., 2017)	
	Job tenure	Learner's years of work experience (van Daal et al., 2014)	
	Culture	Learner's origin or cultural dimension (Hofstede, 1984; K. Li, 2019)	
	Digital literacy	Knowledge, skills, and competences required to interact with digital tools and in (online) learning environments (Tinmaz et al., 2022)	
	General self-regulation	Learner's general tendency toward self-regulation and self-directedness beyond learning (Kyndt et al., 2014; Grant et al., 2002)	
	Big Five personality traits	Extraversion, agreeableness, neuroticism, openness, conscientiousness (McCrae & Costa, 2004)	
	Curiosity	Tendency to seek and embrace new information and experiences (Kashdan et al., 2020)	
	Occupation	Learner's current occupation	
	General attitudes toward learning	Learner's general attitudes and beliefs regarding learning and CE (Schulz & Roßnagel, 2010)	
	Organizational citizenship behavior	Individual behavior that is not directly recognized by a work organization's formal reward system but that promotes the organization's functionality (Organ, 1988; Podsakoff et al., 2000)	
	CE-related factors		
	Peer interaction	Instructional design elements that enable interactions between learners (e.g., discussion forums, group work; Janakiraman et al., 2018)	
	Difficulty	(Perceived) difficulty of the CE activity; degree to which the CE activity is perceived as challenging (Rigolizzo & Zhu, 2021)	
	SRL intervention	Specific interventions (e.g., video instructions) designed to support SRL (Hosseini et al., 2020; Jansen et al., 2020; J. Wong et al., 2019)	

Variable	Codes	Description	Krippendorff's alpha
	Learning content	Characteristics of the learning materials (e.g., topic, format; Vanslambrouck, Zhu, Pynoo, Thomas, et al., 2019)	
	Feedback	Opportunities to receive external feedback on learning progress (Rigolizzo & Zhu, 2021)	
	Self-assessments	Opportunities for self-assessments (e.g., tests, quizzes, problem sets; Janakiraman et al., 2018)	
	Online setting	CE activities delivered online (vs. face-to-face CE activities)	
	Flipped classroom	Type of blended learning in which new instructional content is introduced before class time as a homework activity; during class time, this content is discussed in more depth, and learning activities traditionally constituting homework are moved into the classroom (Akçayır & Akçayır, 2018; Hosseini et al., 2020)	
	Organization and structure	Quality of the CE activity in terms of transparency, organization, and structure (Kim et al., 2021)	
	Transactional distance	Barriers to learners' active engagement with learning, including barriers to learner–learner interaction, learner–instructor interaction, and learner–content interaction (Kim et al., 2021; Paul et al., 2015)	
	Ease of use	Degree to which the learning system is easy to use (Marangunić & Granić, 2015)	
	Duration	Length of the CE activity (e.g., number of learning activities; Janakiraman et al., 2018)	
	Work-related factors		
	Organizational learning culture	Degree to which CE is integrated into the organizational culture; degree to which employees are supported and encouraged to participate in CE activities (Kittel et al., 2021; Marsick & Watkins, 2003)	
	Job control	Learners' potential control over their work tasks and behavior; includes decision authority and possibilities to make use of their own knowledge, skills, and competences to accomplish the work tasks (Gijbels, 2012; Karasek, 1979)	
	Job demands	Stressors within the work environment (e.g., stressors related to work tasks, personal conflicts; Gijbels, 2012; Karasek, 1979)	
	Working area	Learner's working area (e.g., chemistry, crowdwork; Kreber et al., 2005; Margaryan, 2019)	
	Team size	Number of team members in the learner's work team	
	Job involvement	Degree to which learners psychologically identify with their job; degree to which learners value the importance of their job (Decius et al., 2021; Griffin et al., 2010)	
	Task identity	Degree to which the learner's job has a visible outcome in the form of a whole product (Hackman & Oldham, 1975; Kittel et al., 2021)	
	Pay satisfaction	Learners' satisfaction with their salary (Kyndt et al., 2014)	
	Internal employability	Learner's willingness and ability to stay employed within the current organization (Juhdi et al., 2010; Kyndt et al., 2014)	

Variable	Codes	Description	Krippendorff's alpha
	Friendship relationships with coworkers	Number of friends at work (Geller & Bamberger, 2012)	
	Hours of work	Learner's working hours (e.g., full-time vs. part-time; van Daal et al., 2014)	
Method	Quantitative	The relationship between learners' use of SRL strategies and the associated factor was investigated using quantitative methods	1.0
	Qualitative	The relationship between learners' use of SRL strategies and the associated factor was investigated using qualitative methods	
Sample size	Exact sample size	Exact sample size from the study if reported	.86
	N/A	No information on sample size available	
Effect size	Exact effect size	Exact effect size from the study if reported	.96
	N/A	No information on effect size available	
		Moderators [a]	
Operationalization of SRL strategies	Subjective	Self-report measures	.94
	Objective	Behavioral measures	
Operationalization of associated factors	Subjective	Self-report measures	.97
	Objective	Behavioral measures	
Setting	Online	The CE activity took place exclusively online	.94
	Face-to-face	The CE activity included face-to-face sessions	
Work-relatedness	Work-related	CE activity was linked to the learner's job position (Kyndt & Baert, 2013; Schiersmann, 2007)	.88
	Non-work-related	CE activity was not linked to the learner's job position (Demary et al., 2013; Schiersmann, 2007)	
Formality [b]	Formal/non-formal	Organized CE activity (Misko, 2008; Radcliffe & Colletta, 1989; Schumacher, 2018)	.76
	Informal	Unorganized CE activity occurring through experiences in daily (work) life (Eraut, 2004; Schiersmann, 2007; Schumacher, 2018)	
	N/A	No information on formality available	

Note. SRL = self-regulated learning; CE = continuing education.
[a] The moderators were coded only for studies included in the moderator analyses. Operationalization of SRL strategies and associated factors was coded at the effect size level (i.e., values on these moderator variables can differ for different effect sizes within one study). All other moderators were coded at the study level (i.e., values on these moderator variables are identical for all effect sizes within one study). [b] Most studies did not provide sufficient information to differentiate whether the learning activity was formal or non-formal. Therefore, we differentiated between organized (i.e., formal/non-formal) and informal learning activities.

5.4 Self-Regulated Learning Strategies in Continuing Education

Researchers have agreed that learning in CE is different than in K-12 and higher education (Knowles et al., 2012; Tynjälä, 2008; Wozniak, 2020). Therefore, the factors triggering or inhibiting SRL strategies, as well as the relevance of SRL in general and specific SRL strategies in detail, might differ between CE and K-12 as well as higher education. For example, learning in CE often clashes with professional and family commitments, resulting in less priority being given to learning (Eriksson et al., 2017; Schröer et al., 2022). Therefore, specific SRL strategies such as time management should be especially important in CE to help learners balance learning with professional and family commitments (Kizilcec & Halawa, 2015; Nawrot & Doucet, 2014). Even though such conflicting commitments may also occur in K-12 and higher education, they are more prominent in CE. Learning is the main occupation of K-12 and full-time higher education students. Thus, learning tasks may be given higher priority than in CE, which usually happens besides the learners' main occupation (e.g., work; Eriksson et al., 2017; Schröer et al., 2022).

Moreover, learning in K-12 and higher education usually occurs through formal learning activities, whereas learning in CE often occurs through non-formal and informal learning activities in addition to formal learning activities (Schiersmann, 2007; Tynjälä, 2008). While some researchers have argued that the major assumptions of SRL theories might be equally applied to formal, non-formal, and informal learning activities (Kittel et al., 2021; Lee et al., 2020a), other researchers have argued that SRL strategies should play a more important role in informal learning activities due to their unstructured and unorganized nature (Beishuizen & Steffens, 2011).

Knowles et al. (2012) introduced adult learning theory to highlight that adult learners in CE differ from younger learners in K-12 and higher education. According to adult learning theory, learners in CE are distinguished by a strong need for self-direction. They want to be treated as responsible individuals capable of controlling their own learning and resist when others try to force their will upon them (Knowles, 1985; Knowles et al., 2012; Manning, 2007). Accordingly, in contrast to K-12 and higher education, learners in CE are usually given a higher degree of autonomy to decide when, how, and what they would like to learn (Sitzmann & Ely, 2011). Hence, learners in CE need to apply SRL strategies to deal with the autonomy they are granted (Jansen et al., 2020; Sitzmann & Ely, 2011). However, in some cases of work-related CE, learning activities might also be mandatory and externally regulated by the employer. These learning activities are characterized by low degrees of learner autonomy (Hemmler et al., 2023), raising the question of whether SRL might play a different role in these types of CE.

Thus, the factors triggering, inhibiting, and interacting with SRL strategies in CE still remain unclear and need to be investigated in a comprehensive systematic review and meta-analysis. SRL theories have suggested that SRL results from an interaction between motivational states and behavioral variables related to the learning process, individual characteristics, and characteristics of the learning environment (Pintrich, 2000; Winne, 2011;

Zimmerman, 1989, 2013). The learning environment in CE may be shaped by characteristics of the CE activity as well as learners' work environment (Alonso-Mencía et al., 2020; van Houten-Schat et al., 2018). Therefore, we suggest that learning process-related, learner-related, CE-related, and work-related factors may be associated with SRL strategies in CE.

5.4.1 Learning Process-Related Factors

Learning process-related factors describe variables related to learners' behavior, motivational states, and performance during participation in a specific CE activity (Greene & Azevedo, 2007; Yau & Ifenthaler, 2020). In several SRL theories (e.g., Pintrich, 2000; Zimmerman & Schunk, 2007), learning process-related factors (e.g., achievement motivation, learning performance) have been considered antecedents and outcomes of SRL strategies. For example, SRL strategies require time and effort (Zimmerman & Schunk, 2007). Therefore, achievement motivation has been considered a precondition for SRL strategies (Pintrich, 2000; Winne, 2011; Zimmerman & Schunk, 2007). Further, learning performance in CE relies on learners' ability to autonomously monitor and control their learning processes and resources, which is reflected by SRL strategies (Kittel et al., 2021; Pintrich, 2000).

In their systematic review, Lee et al. (2019) showed positive effects of SRL strategies on achievement motivation, learning performance, and goal achievement in MOOCs. Such relationships were also found in Sitzmann and Ely's (2011) meta-analysis focusing on higher education and work-related, formal CE. However, it remains unclear whether and to what extent these relationships also apply to other types of CE. Empirical primary studies focusing on different types of CE have shown a considerable variance of effect sizes (e.g., Chen & Jang, Jo et al., 2015; Littlejohn, Milligan, et al., 2016; Lourenco & Ferreira, 2019). Moreover, it remains unclear what other learning process-related factors are linked to SRL strategies in CE. Empirical primary studies have suggested that further learning process-related factors, such as learner engagement (Kizilcec et al., 2017), learner satisfaction (Lee et al., 2020a), or completion of the CE activity (Handoko et al., 2019), might be associated with SRL strategies in CE.

5.4.2 Learner-Related Factors

Learner-related factors describe learners' general dispositions and beliefs in relation to CE (Greene & Azevedo, 2007; Winne, 2022). SRL researchers have suggested that different learners exposed to the same learning context might engage in SRL differently due to individual differences (Greene & Azevedo, 2007; Winne, 1996). In a systematic review focusing on MOOCs and online higher education, J. Wong et al. (2019) showed that learners' cognitive ability, gender, and prior knowledge influenced the effectiveness of SRL interventions. Another systematic review identified several learner-related factors (e.g., reflective skills, previous experiences) associated with medical students' and residents' use of SRL strategies (van Houten-Schat et al., 2018). However, systematic reviews and meta-analyses investigating learner-related factors with a broader focus on CE are missing. Empirical primary studies have suggested that further learner-related factors, such as age (Haemer et al., 2017) and personality traits (van Daal et al., 2014), might be associated with SRL strategies in CE.

5.4.3 Continuing Education-Related Factors

CE-related factors refer to instructional characteristics and learners' perceptions of the CE activity (Alonso-Mencía et al., 2020; Hemmler & Ifenthaler, 2022). According to Pintrich (2000), SRL is guided and constrained by contextual characteristics of the learning activity (e.g., learning tasks, classroom climate). Such characteristics may influence how learners operate on learning materials and what SRL strategies they apply (Winne, 2011, 2022; Winne & Hadwin, 1998). In their systematic review focusing on MOOCs, Alonso-Mencía et al. (2020) revealed that the need for SRL strategies increased with the length of the MOOC and that learners' use of SRL strategies may be influenced by course design and delivery mode. Further systematic reviews summarized interventions (e.g., prompts, feedback) designed to trigger SRL strategies in MOOCs and online higher education (e.g., J. Wong et al., 2019). These CE-related factors identified in previous systematic reviews on MOOCs need to be complemented by a broader view on CE, as empirical primary studies have revealed further CE-related factors (e.g., peer interaction) associated with SRL strategies in CE activities other than MOOCs (e.g., Vanslambrouck, Zhu, Pynoo, Thomas, et al., 2019).

5.4.4 Work-Related Factors

Work-related factors describe job characteristics and learners' perceptions of their work environment (Hemmler & Ifenthaler, 2022). As CE may be directly linked to learners' job position (Demary et al., 2013; Schiersmann, 2007), researchers have suggested that work-related factors may influence SRL (Gijbels et al., 2012; Kittel et al., 2021). For example, job control and job demands have been associated with SRL strategies in empirical primary studies (e.g., Gijbels et al., 2012; Raemdonck et al., 2014). However, a comprehensive list of work-related factors triggering or inhibiting SRL strategies in CE is missing.

5.4.5 Potential Moderators

Researchers have argued that methodological features (e.g., operationalization of variables) might impact SRL (Hadwin et al., 2007; Winne & Hadwin, 1998) and that the relevance of specific SRL strategies might differ for different types of learning activities (e.g., online vs. face-to-face, formal vs. informal learning activities; Beishuizen & Steffens, 2011; Broadbent & Poon, 2015). However, research investigating how methodological features and the type of CE activity moderate the relationships between SRL strategies and learning process-related, learner-related, CE-related, and work-related factors is lacking. Therefore, we employed the following variables as potential moderators.

Operationalization of Variables

In empirical studies, SRL strategies can be measured subjectively using self-report questionnaires (e.g., Barnard et al., 2009; Pintrich et al., 1991) or objectively using behavioral measures, such as trace data in online learning environments (Araka et al., 2020; Winne, 2022). Moreover, several learning process-related, learner-related, CE-related, and work-related factors can be measured subjectively (e.g., self-reported learning performance; Schulz & Roßnagel, 2010) or objectively (e.g., learning performance measured by knowledge tests; Tang, 2021). Learners' subjective experiences may differ from objective measures, and, therefore, the operationalization of variables might affect the relationships between SRL strategies and learning process-related, learner-related, CE-related, as well as work-related factors (Aeon & Aguinis, 2017; Hadwin et al., 2007; Tempelaar et al., 2020).

Setting

Online CE provides high degrees of autonomy and flexibility to learners. In contrast to (classroom-based) face-to-face learning activities, where all learners learn at the same place and time, online CE is often self-paced (Broadbent & Poon, 2015; Fan et al., 2021). Consequently, the need for SRL strategies might be higher in online than in face-to-face CE activities (Broadbent & Poon, 2015; Nawrot & Doucet, 2014). Thus, the setting of the CE activity might moderate the relationships between SRL strategies and potential antecedents and outcomes.

Work-Relatedness

In contrast to non-work-related CE, work-related CE may be mandatory and externally regulated by the employer. If the employer decides what and when should be learned, learners may have fewer possibilities to self-regulate their learning (Hemmler et al., 2023). Thus, the work-relatedness of the CE activity might have an impact on learners' need for SRL strategies and the strength of the relationships between learners' use of SRL strategies and potential antecedents and outcomes.

Formality

Since informal learning activities are not organized by external entities (Eraut, 2004; Schumacher, 2018), they might require a stronger need for SRL strategies than non-formal and formal learning activities (Beishuizen & Steffens, 2011). Thus, the formality of the CE activity might affect the relationships between SRL strategies and learning process-related, learner-related, CE-related, as well as work-related factors.

5.5 Research Questions

Based on the research discussed above, we formulated the following research questions:

1. What learning process-related, learner-related, CE-related, and work-related factors have been associated with learners' use of SRL strategies in empirical studies focusing on CE?
2. To what extent are these factors related to learners' use of SRL strategies in CE?
3. To what extent do methodological features (i.e., operationalization of variables) and the type of the CE activity (i.e., setting, work-relatedness, formality) moderate these relationships?

5.6 Method

5.6.1 Search Strategies

We developed a research protocol describing search strategies, inclusion criteria, and definitions of key terms. All members of the research team were familiarized with the research protocol in a training session conducted by the first author of this paper. To identify empirical studies that investigated SRL strategies in CE, several search strategies were performed by the first author of this paper and one trained research assistant. First, we conducted an electronic search in the databases Educational Resources Information Center (via ProQuest), psycArticles, psycINFO, and PSYNDEX (via EBSCOhost) using the search string presented in Table 5-2. The database search was conducted between April 4, 2022, and April 11, 2022. Second, we conducted a manual search of the list of publications included in Sitzmann and Ely's (2011) meta-analysis. Third, we conducted a manual search of the reference lists of a selection of relevant publications that were identified through the database search. To be precise, the reference lists of the following publications were searched: Agonács et al. (2020), Birenbaum and Rosenau (2006), Chen and Jang (2019), and Lourenco and Ferreira (2019). The search strategies yielded a total number of 13,465 publications.

Table 5-2

Search String for Search in Databases

Topic	Search terms
SRL	("self-regulated learning" OR "self-regulation" OR "self-directed learning" OR "learning strateg*" OR "cognitive strateg*" OR "metacognit*" OR "resource management strateg*" OR "resource strateg*" OR "time and study environment" OR "time management" OR "environm* structuring" OR "effort regulation" OR "peer learning" OR "help seeking" OR "goal setting" OR "self-evaluation" OR "self-reflection" OR "self-control" OR "self-observation" OR "self-management" OR "self-monitoring" OR "task strateg*")
AND	
CE	("continuing education" OR "further education" OR "workplace learning" OR "work-related learning" OR "work-based learning" OR "employee learning" OR "employee training" OR "employee development" OR "professional development" OR "professional training" OR "vocational education" OR "vocational training" OR "VET" OR "lifelong learning" OR "lifelong education" OR "continuous learning" OR "adult education" OR "Massive Open Online Course*" OR "MOOC*" OR "on-the-job training" OR "off-the-job training" OR "near-the-job training" OR "operational training" OR "corporate training")

Note. We did not restrict the database search to a specific part of a publication (i.e., the combinations of search terms could appear anywhere in a document). SRL = self-regulated learning; CE = continuing education.

5.6.2 Publication Screening

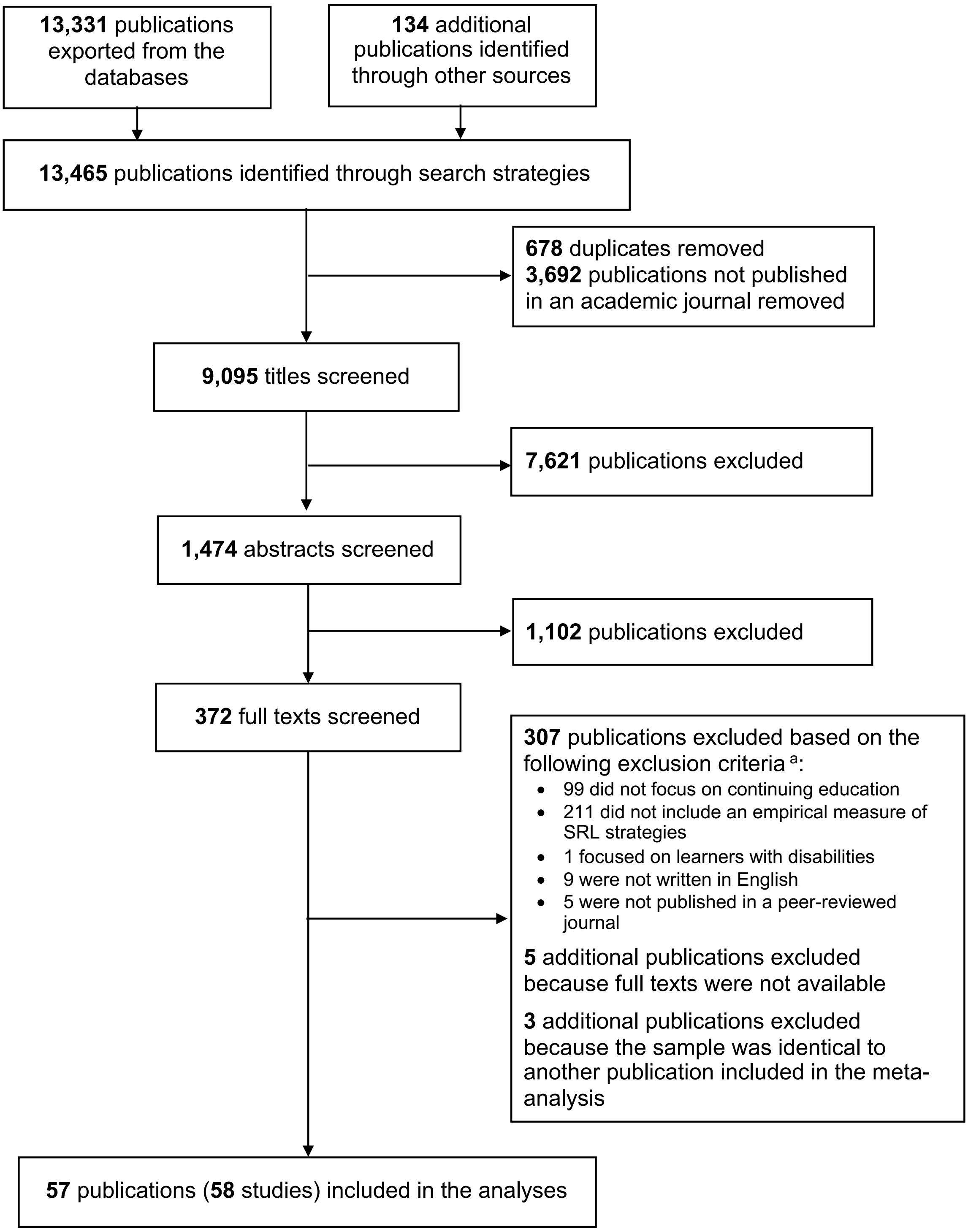
Figure 5-1 presents an overview of the publication screening process. First, duplicates and publications not published in an academic journal were removed by the first author of this paper through an automatic search in Microsoft Excel. Then, titles, abstracts, and full texts of the remaining publications were screened for the inclusion and exclusion criteria presented in Table 5-3. Titles, abstracts, and full texts were divided among and screened by the first author of this paper and one trained research assistant. Fifty-seven publications containing $m = 58$ studies were identified as eligible for our systematic review and meta-analysis. The total sample size of all included studies was $N = 48{,}213$ learners.

5.6.3 Coding Procedures

All factors associated with SRL strategies in CE were inductively extracted from the primary studies and assigned to one of the following four main categories: learning process-related, learner-related, CE-related, or work-related factors. Further information on the relationships between these factors and the associated SRL strategies was coded (e.g., method, effect size; see Table 5-1). The first author of this paper initially coded all studies and developed a coding manual. Then, a research assistant who was given two hours of additional training independently coded all studies for verification. An overview of the coding manual and intercoder reliability is shown in Table 5-1. Differences between coders were resolved by discussion.

Figure 5-1

Flow Diagram of the Publication Screening Process



Note. SRL = self-regulated learning.

[a] Some publications were excluded for multiple reasons. Therefore, the sum of publications across all exclusion criteria is greater than 307.

Table 5-3

Inclusion and Exclusion Criteria

Inclusion criterion	Exclusion criterion	Justification/Explanation
The study focused on CE.	The study did not focus on CE but on a different educational context (e.g., K-12 or higher education).	CE is the primary focus of our systematic review and meta-analysis. For studies in which only part of the sample focused on CE and the other part focused on another educational context, only the sample focusing on CE was included.
The study reported an empirical measure (quantitative and/or qualitative) of SRL strategies.	The study did not include an empirical measure of SRL strategies.	Information on SRL strategies was needed to answer our research questions. Interventions to support SRL strategies were not considered as a measure of SRL strategies, as these interventions might have influenced other constructs and may not adequately represent SRL (Davis et al., 2016; J. Wong et al., 2021).
The study investigated SRL strategies in relation to other variables.	The study focused exclusively on SRL strategies.	Information on variables associated with SRL strategies was needed to answer our research questions.
The study focused on learners without disabilities.	The study focused on learners with disabilities.	Learners with disabilities may have different approaches to SRL than learners without disabilities (Klassen, 2010).
The study was written in English.	The study was not written in English.	Restrictions based on language were necessary because of the language proficiency of the research team. We decided to focus on studies published in English as the international language of science (Drubin & Kellogg, 2012).
The study was published in a peer-reviewed journal.	The study was not published in a peer-reviewed journal.	The quality of a meta-analysis depends on the quality of the included primary studies (Egger et al., 2001). To guarantee a minimum level of quality of primary studies, we decided to exclude studies not published in a peer-reviewed journal.

Note. SRL = self-regulated learning; CE = continuing education.

5.6.4 Meta-Analytic Procedures

Meta-analyses were conducted to answer Research Question 2 and Research Question 3. Zero-order correlations *r* were used as a common effect size measure. If zero-order correlations were not reported, they were calculated from available descriptive statistics or converted from other effect sizes. Authors of the studies were contacted if studies did not provide sufficient information to compute zero-order correlations. If the authors did not respond or could not provide the information required, these studies were excluded from the meta-analyses. Following the approach of Tayfur et al. (2021), we conducted meta-analyses for each learning process-related, learner-related, CE-related, and work-related factor for which zero-order correlations with SRL strategies were available from at least three studies. Consequently, meta-analyses for the relationships between SRL strategies and the following

13 factors were conducted: achievement motivation, learning performance, learner engagement, learner satisfaction, avoidance behavior, age, educational level, prior knowledge, job tenure, CE experience, organizational learning culture, job control, and job demands.

Three-Level Meta-Analytic Models

Since some studies reported several effect sizes for one relationship, independency of effect sizes was not given. To deal with the dependency of effect sizes, we followed the guidelines proposed by Assink and Wibbelink (2016) and deployed random-effects three-level meta-analytic models that included three variance components: sampling variance (level 1), within-study variance (level 2), and between-study variance (level 3). We used the metafor package (Viechtbauer, 2010) for R (version 4.3.0) to implement our three-level meta-analytic models. As recommended by Assink and Wibbelink (2016), the models were fitted using restricted maximum-likelihood estimation, and a *t*-distribution was used to compute *p*-values and confidence intervals of the average correlations. Significance levels were set at .05. As recommended by Borenstein et al. (2009), zero-order correlations *r* were transformed into Fisher's *z* for analyses. Due to distribution characteristics, correlations *r* might introduce bias when the standard error for studies with small sample sizes is estimated (Alexander et al., 1989; Harrer et al., 2021). For interpretation of the meta-analytic results, Fisher's *z* scores were back-transformed into *r* and interpreted using Cohen's (1988) classification.

For each of the 13 factors (i.e., achievement motivation, learning performance, etc.), we conducted meta-analyses including all measures of SRL strategies provided in the primary studies (in the following referred to as *pooled* meta-analyses). If studies reported different measures of SRL strategies and a composite score summarizing these different measures, only the composite score was included in the pooled meta-analyses to avoid double-counting effect sizes. In the next step, we tested whether the average correlations differed for different measures of SRL strategies. We conducted additional meta-analyses for measures of cognitive, metacognitive, resource management, and composite scores of SRL strategies as well as for each of the specific SRL strategies (e.g., rehearsal, goal setting and planning) presented in Table 5-1. To ensure meaningful analyses, the meta-analyses for the different SRL strategies, as well as the subsequent moderator analyses, were conducted only for factors for which zero-order correlations *r* with cognitive, metacognitive, resource management, and composite scores of SRL strategies were available from at least three studies. Consequently, meta-analyses for different SRL strategies and moderator analyses were conducted for achievement motivation, learning performance, learner engagement, learner satisfaction, and organizational learning culture.

Measures of Heterogeneity and Publication Bias

We addressed heterogeneity in effect sizes using the *Q*-test and the I^2 statistic. In three-level meta-analytic models, two values of I^2 need to be considered because the heterogeneity variance is composed of two parts: the proportion of variance attributable to level 2 (within-study variance, represented by I^2_{within}) and the proportion of variance attributable to level 3 (between-study variance, represented by I^2_{between}; Assink & Wibbelink, 2016). Pooled meta-analyses were tested for publication bias using funnel plots and a three-level version of the Egger's regression test (Fernández-Castilla et al., 2021; Rodgers & Pustejovsky, 2021). The original Egger's regression test (Egger et al., 1997) has been developed for two-level meta-analyses assuming independency of effect sizes. Research has shown that ignoring dependency of effect sizes when employing Egger's regression test may lead to inflated Type I error rates (Rodgers & Pustejovsky, 2021). Therefore, we deployed a three-level version of the Egger's regression test whereby the estimated standard error of Fisher's *z* was added as an independent variable in a three-level meta-regression, including between-study and within-study variance. A significant regression coefficient for the standard error $b_{\text{SE\_z}}$ indicated funnel plot asymmetry (Fernández-Castilla et al., 2021; Rodgers & Pustejovsky, 2021).

Moderator Analyses

Moderators were tested by adding them as independent variables in a three-level multiple meta-regression. We performed moderator analyses for the pooled meta-analyses as well as the meta-analyses focusing on cognitive, metacognitive, resource management, and composite scores of SRL strategies. Moderator analyses were not performed for the specific SRL strategies (e.g., rehearsal, goal setting and planning) presented in Table 5-1 due to the limited number of primary studies. We employed multiple meta-regression analyses to test all moderators simultaneously. As such, the unique effect of each moderator can be tested, controlling for the other moderators in the model (Assink & Wibbelink, 2016). To increase the reliability of moderator analyses, moderators were included in the meta-regression only if at least three zero-order correlations *r* were available for each coded category of the moderator (see also moderator analyses conducted by J.-B. Li et al., 2021).

5.7 Results

5.7.1 Included Studies and Publication Bias

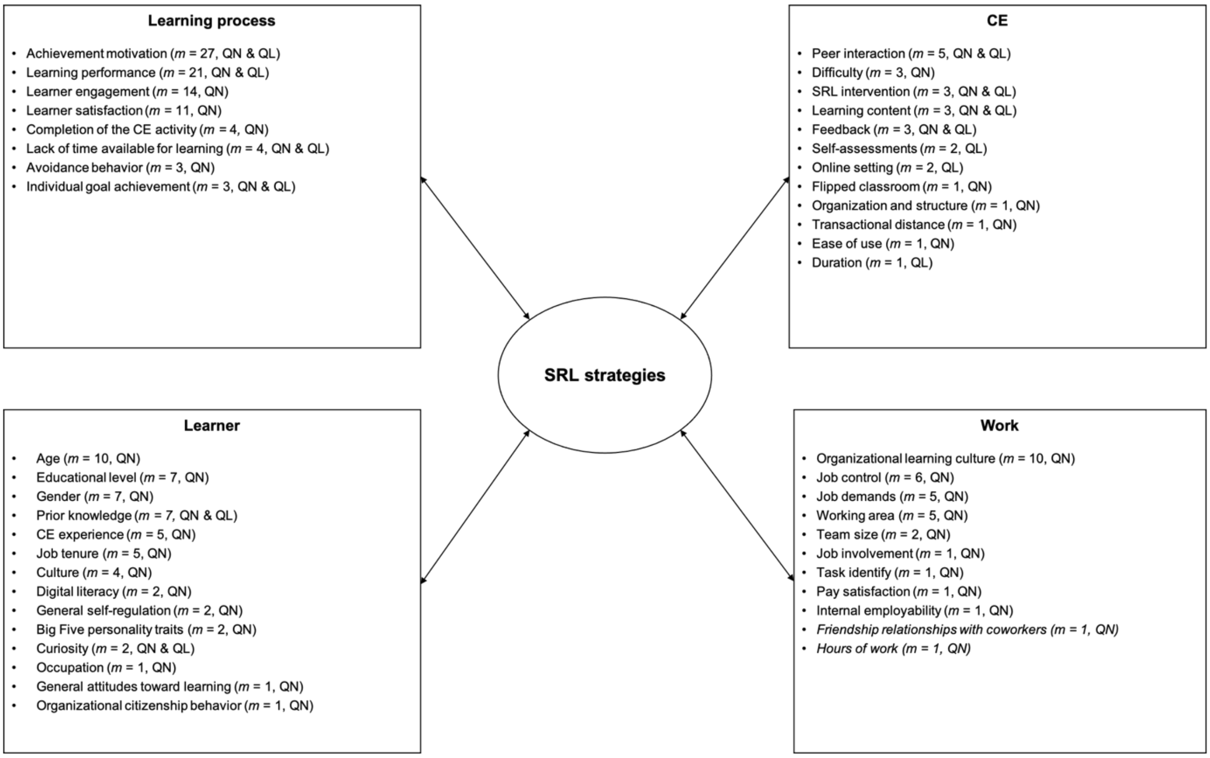
An overview of all studies included in our investigations is presented in Appendix C (for a detailed description of the effect sizes included in the meta-analyses, see Online Supplemental Materials). Funnel plots and the results of the three-level version of the Egger's regression test can also be found in Appendix C. No statistically significant asymmetry in funnel plots was detected.

5.7.2 Research Question 1: Factors Associated With Self-Regulated Learning Strategies

Figure 5-2 provides an overview of all factors associated with learners' use of SRL strategies in the included primary studies.

Figure 5-2

Factors Associated With Self-Regulated Learning Strategies in Continuing Education



Note. All factors investigated using quantitative methods were significant in at least one study, except for friendship relationships with coworkers and hours of work (marked in italics), for which no significant effects were found. SRL = self-regulated learning; CE = continuing education; QN = relationship with SRL strategies was investigated using quantitative methods; QL = relationship with SRL strategies was investigated using qualitative methods.

Learning Process-Related Factors

In several studies, SRL strategies were positively associated with achievement motivation (e.g., Chung, 2015; Lee et al., 2020b; Zhu et al., 2020), learning performance (e.g., Moraes & Borges-Andrade, 2015; Wan et al., 2012), learner engagement (e.g., Fontana et al., 2015; Siadaty et al., 2016), learner satisfaction (e.g., Lourenco & Ferreira, 2019; Tsai et al., 2018), completion of the CE activity (e.g., Guajardo Leal, 2019; Hughes, 2019), and individual goal achievement (e.g., Kizilcec et al., 2017; Kormos & Csizér, 2014), as well as negatively associated with avoidance behavior (e.g., Schulz & Roßnagel, 2010; van Daal et al., 2014).

Lack of time available for learning was identified as a barrier to learners' use of cognitive (Hosseini et al., 2020; Rabin et al., 2020), metacognitive (Hosseini et al., 2020; Milligan & Littlejohn, 2016; Rabin et al., 2020), and peer learning (Milligan & Littlejohn, 2016) strategies. Consequently, effective time management was identified as a prerequisite for other SRL strategies (Milligan & Littlejohn, 2016). Time management strategies were considered especially important for learners with professional and family commitments (e.g., child care) limiting learners' time available for learning (Vanslambrouck, Zhu, Pynoo, Thomas, et al., 2019).

Learner-Related Factors

The studies that examined learner-related factors mainly sought to identify relationships between SRL strategies and demographic variables (e.g., age, educational level; Alonso-Mencía et al., 2021; Martinez-Lopez et al., 2017; Schulz & Roßnagel, 2010) as well as learners' prior knowledge and experiences (e.g., job tenure, CE experience; Haemer et al., 2017; Warr & Bunce, 1995). The findings of these studies varied regarding the strength and direction of the relationships. Some studies identified positive relationships between SRL strategies and personality traits (e.g., curiosity; Decius et al., 2021) as well as general attitudes toward learning (Schulz & Roßnagel, 2010).

Continuing Education-Related Factors

Several instructional methods, such as peer interaction (Haemer et al., 2017), feedback (Kittel et al., 2021), self-assessments (Janakiraman et al., 2018), and flipped classroom (Hosseini et al., 2020), were positively associated with SRL strategies in the included primary studies. SRL strategies were considered more important the longer the duration of the CE activity (Janakiraman et al., 2018) and for CE activities delivered online than for face-to-face CE activities (Milligan & Littlejohn, 2016; Vanslambrouck, Zhu, Pynoo, Thomas, et al., 2019). Some studies (e.g., Jansen et al., 2020; J. Wong et al., 2021) investigated interventions for supporting SRL strategies in online learning environments. However, the impact of these interventions on SRL strategies was limited (Jansen et al., 2020; J. Wong et al., 2021). Vanslambrouck, Zhu, Pynoo, Thomas, et al. (2019) revealed that the learning content (e.g., the format of the content) might influence learners' choice of cognitive strategies. Further, SRL strategies were positively associated with perceived difficulty (e.g., Rigolizzo & Zhu, 2021; Warr et al., 1999), organization and structure (Kim et al., 2021), transactional distance (Kim et al., 2021), and ease of use (Lin et al., 2018) of the CE activity.

Work-Related Factors

In several studies, an organizational learning culture supporting learners' engagement in CE activities (e.g., Decius et al., 2021; Kittel et al., 2021) as well as job control (e.g., Gijbels et al., 2012; Straka, 2000), job demands (e.g., Raemdonck et al., 2014; Wan et al., 2012), team size (Geller & Bamberger, 2012), job involvement (Decius et al., 2021), task identity (Kittel et al., 2021), pay satisfaction (Kyndt et al., 2014), and internal employability (Kyndt et al., 2014) were positively associated with SRL strategies in the included primary studies. Weak and partially nonsignificant relationships between SRL strategies and working area (e.g., Haemer et al., 2017; Margaryan, 2019), hours of work (van Daal et al., 2014), and friendship relationships with coworkers (Geller & Bamberger, 2012) were identified.

5.7.3 Research Question 2: Strength of the Relationships

Pooled Meta-Analyses

The results of the pooled meta-analyses are presented in Table 5-4. Significant relationships between SRL strategies and all learning process-related variables included in the pooled meta-analyses were detected. The average correlation coefficient indicated a weak negative relationship for avoidance behavior ($r = -.14$), moderate positive relationships for achievement motivation ($r = .30$) and learner satisfaction ($r = .30$), as well as moderate to strong positive relationships for learning performance ($r = .36$) and learner engagement ($r = .39$). No significant relationships between SRL strategies and the learner-related variables age, educational level, and job tenure were detected. The average correlations for prior knowledge ($r = .05$) and CE experience ($r = .08$) were significant but weak. Significant positive relationships between SRL strategies and all work-related variables included in the pooled meta-analyses were detected. The average correlation coefficients indicated a weak to moderate relationship for job demands ($r = .21$) and moderate relationships for organizational learning culture ($r = .26$) and job control ($r = .28$).

Analyses for Different SRL Strategies

Tables 5-5–5-9 show the meta-analytic results for the relationships between different SRL strategies and achievement motivation (Table 5-5), learning performance (Table 5-6), learner engagement (Table 5-7), learner satisfaction (Table 5-8), and organizational learning culture (Table 5-9). Average correlation coefficients for achievement motivation indicated a weak to moderate relationship with resource management strategies ($r = .24$), moderate relationships with cognitive ($r = .28$) and metacognitive ($r = .30$) strategies, as well as a moderate to strong relationship with composite scores of SRL strategies ($r = .39$). Average correlation coefficients for learning performance showed a weak to moderate relationship with cognitive strategies (*r* = .16), a moderate relationship with resource management strategies (*r* = .29), a moderate to strong relationship with metacognitive strategies (*r* = .44), and a strong relationship with composite scores of SRL strategies (*r* = .48). For learner engagement, average correlation coefficients indicated a moderate relationship with cognitive strategies (*r* = .30), a moderate to strong relationship with metacognitive strategies (*r* = .35), and a strong relationship with composite scores of SRL strategies (*r* = .46). The relationship between resource management strategies and learner engagement was not significant. For learner satisfaction, average correlation coefficients indicated a weak to moderate relationship with resource management strategies (*r* = .20) as well as moderate relationships with cognitive (*r* = .26), metacognitive (*r* = .33), and composite scores of SRL (*r* = .27) strategies. Regarding organizational learning culture, weak to moderate relationships with cognitive strategies (*r* = .15) and resource management strategies (*r* = .23), as well as moderate relationships with metacognitive (*r* = .27) and composite scores of SRL (*r* = .27) strategies, were detected.

5.7.4 Research Question 3: Moderator Analyses

As shown in Table 5-10, operationalization of variables, setting, and work-relatedness were detected as significant moderators. The relationship between SRL strategies and achievement motivation was significantly stronger for subjective measures of SRL strategies than for objective measures in the pooled meta-analysis and in the meta-analysis focusing on metacognitive strategies. Further, the relationship between SRL strategies and learner satisfaction was significantly stronger for subjective than for objective measures of SRL strategies in the pooled meta-analysis and in the meta-analyses focusing on metacognitive and resource management strategies. The relationship between cognitive strategies and learner engagement was significantly stronger for subjective measures of learner engagement than for objective measures. The relationship between metacognitive strategies and achievement motivation was stronger for CE activities delivered completely online than for CE activities that included face-to-face sessions. Finally, the relationship between resource management strategies and achievement motivation was stronger for non-work-related than for work-related CE activities. All other moderator analyses were not significant. Results of the omnibus tests of moderators and the amounts of residual heterogeneity not explained by the moderators are presented in Table 5-11.

Table 5-4

Results for the Pooled Meta-Analyses: Relationships Between Self-Regulated Learning Strategies and Associated Factors

Associated factor	*k*	*m*	*n*	*r*	95% CI for *r*		Heterogeneity		
					LL	UL	*Q*(*df*)	I^2_{within}	$I^2_{between}$
Learning process-related factors									
Achievement motivation	195	24	7,267	$.30^{***}$	.24	.35	$1,567.15(194)^{***}$	46.86	42.27
Learning performance	61	15	13,745	$.36^{***}$	.23	.47	$1,874.50(60)^{***}$	30.10	67.33
Learner engagement	79	12	9,504	$.39^{***}$	.25	.51	$1,768.89\ (78)^{***}$	11.11	89.93
Learner satisfaction	29	7	1,133	$.30^{***}$	.17	.41	$88.67(28)^{***}$	7.35	65.65
Avoidance behavior	6	3	675	$-.14^{**}$	−.22	−.06	$9.79(5)^{\dagger}$	50.86	0.00
Learner-related factors									
Age	22	8	19,190	.00	−.09	.09	$185.07(21)^{***}$	18.99	77.68
Educational level	19	6	18,598	$.03^{\dagger}$	−.00	.06	$64.09(18)^{***}$	83.88	0.00
Prior knowledge	14	5	17,595	$.05^{**}$	.02	.07	$76.59(13)^{***}$	81.95	0.00
Job tenure	13	5	1,887	−.01	−.16	.14	$111.97(12)^{***}$	25.88	65.60
CE experience	20	4	18,080	$.08^{*}$	.00	.16	$292.04(19)^{***}$	24.16	71.50
Work-related factors									
Organizational learning culture	39	10	4,189	$.26^{***}$	.17	.34	$247.70(38)^{***}$	12.94	71.17
Job control	13	5	1,433	$.28^{***}$	.23	.33	10.07(12)	0.00	15.43
Job demands	7	5	2,006	$.21^{*}$	.01	.40	$84.62(6)^{***}$	0.00	90.61

Note. Meta-analyses were not conducted for gender and working area, although effect sizes were reported in at least three studies, because these factors were categorical in all included primary studies and sufficient information to calculate the standard error of the standardized mean differences was not available. Moreover, working area was operationalized too differently across studies to meaningfully summarize effect sizes in a meta-analysis. *k* = number of effect sizes; *m* = number of primary studies; *n* = total sample size; *r* = average correlation; CI = confidence interval; LL = lower limit; UL = upper limit. $^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table 5-5

Achievement Motivation: Results for Different Self-Regulated Learning Strategies

SRL strategies	*k*	*m*	*n*	*r*	95% CI of *r*		Heterogeneity		
					LL	UL	*Q*(*df*)	I^2_{within}	$I^2_{between}$
Cognitive strategies	**46**	**13**	**3,594**	**.28*****	**.19**	**.36**	**471.85(45)*****	**39.10**	**50.40**
Rehearsal [a]	2	2	621	.28	−1.0	1.0	33.99(1)***	—	97.06
Elaboration	8	5	1,472	.35*	.07	.58	148.59(7)***	4.21	91.19
Organization [a]	2	2	621	.35	−.95	.99	14.89(1)***	—	93.29
Critical thinking	4	3	791	.39**	.22	.54	6.60(3)†	0.00	60.88
Other	30	8	2,122	.27***	.17	.36	213.97(29)***	41.39	45.16
Metacognitive strategies	**85**	**15**	**3,604**	**.30*****	**.22**	**.37**	**559.89(84)*****	**37.33**	**50.16**
Goal setting and planning	23	8	2,094	.30***	.20	.40	156.31(22)***	46.07	41.71
Self-monitoring	6	2	578	.36**	.23	.48	16.13(5)**	69.25	0.00
Self-evaluation and reaction	32	9	2,499	.27***	.13	.39	264.22(31)***	14.60	75.91
Self-satisfaction	4	2	532	.40***	.31	.48	2.13(3)	0.00	0.00
Metacognitive self-regulation	20	8	1,715	.34***	.29	.40	74.66(19)***	76.75	0.00
Resource management strategies	**81**	**14**	**4,478**	**.24*****	**.17**	**.30**	**572.81(80)*****	**56.23**	**31.18**
Time and study environment	19	7	3,102	.27***	.19	.34	112.92(18)***	82.22	4.88
Effort regulation	17	7	2,896	.23*	.01	.43	268.35(16)***	4.75	89.46
Help seeking	19	7	2,172	.20**	.08	.31	94.09(18)***	12.70	71.61
Peer learning [a]	2	2	621	.29	−.82	.94	6.58(1)*	—	84.79
Other	24	5	843	.26***	.19	.33	57.94(23)***	43.59	22.36
Composite score	**21**	**11**	**2,958**	**.39*****	**.29**	**.48**	**271.30(20)*****	**52.28**	**37.90**

Note. SRL = self-regulated learning; *k* = number of effect sizes; *m* = number of primary studies; *n* = total sample size; *r* = average correlation; CI = confidence interval; LL = lower limit; UL = upper limit.

[a] A traditional two-level meta-analysis (variance components: sampling variance and variance between studies) was performed because only one effect size was reported per study (restricted maximum-likelihood and the Knapp and Hartung, 2003 method were used to compute the models).

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table 5-6

Learning Performance: Results for Different Self-Regulated Learning Strategies

SRL strategies	*k*	*m*	*n*	*r*	95% CI of *r*		Heterogeneity		
					LL	UL	*Q*(*df*)	I^2_{within}	$I^2_{between}$
Cognitive strategies	**19**	**7**	**2,183**	**.16****	**.07**	**.25**	**215.82(18)*****	**84.19**	**5.88**
Rehearsal	5	2	1,216	.10	−.24	.41	47.66(4)***	29.83	64.01
Elaboration	—	—	—	—	—	—	—	—	—
Organization	—	—	—	—	—	—	—	—	—
Critical thinking	—	—	—	—	—	—	—	—	—
Other	13	6	2,092	.20**	.08	.31	149.48(12)***	82.74	6.58
Metacognitive strategies	**18**	**6**	**2,024**	**.44*****	**.26**	**.59**	**374.49(17)*****	**21.94**	**72.59**
Goal setting and planning [a]	4	4	808	.45†	−.03	.76	67.68(3)***	—	95.54
Self-monitoring [a]	2	2	523	.49	−.99	1.0	27.54(1)***	—	96.37
Self-evaluation and reaction	11	6	2,024	.43***	. 31	.53	152.94(10)***	90.55	0.00
Self-satisfaction	—	—	—	—	—	—	—	—	—
Metacognitive self-regulation	—	—	—	—	—	—	—	—	—
Resource management strategies	**31**	**9**	**11,161**	**.29****	**.10**	**.47**	**559.84(30)*****	**22.62**	**74.92**
Time and study environment	4	2	394	.49	−.40	.90	103.53(3)***	51.30	46.48
Effort regulation	4	2	357	.46	−.89	.98	194.54(3)***	0.09	99.03
Help seeking	15	5	10,449	.19*	.03	.35	183.46(14)***	25.87	69.67
Peer learning	—	—	—	—	—	—	—	—	—
Other	8	3	481	.21†	−.05	.45	32.81(7)***	1.18	82.66
Composite score	**8**	**5**	**2,436**	**.48****	**.28**	**.65**	**160.48(7)*****	**9.90**	**84.91**

Note. Dashes indicate that no meta-analysis was performed due to the limited number of primary studies. SRL = self-regulated learning; *k* = number of effect sizes; *m* = number of primary studies; *n* = total sample size; *r* = average correlation; CI = confidence interval; LL = lower limit. UL = upper limit.

[a] A traditional two-level meta-analysis (variance components: sampling variance and variance between studies) was performed because only one effect size was reported per study (restricted maximum-likelihood and the Knapp and Hartung, 2003 method were used to compute the models).

$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table 5-7

Learner Engagement: Results for Different Self-Regulated Learning Strategies

SRL strategies	*k*	*m*	*n*	*r*	95% CI of *r*		Heterogeneity		
					LL	UL	$Q(df)$	I^2_{within}	$I^2_{between}$
Cognitive strategies	**13**	**5**	**5,722**	**.30***	**.01**	**.54**	**203.60(12)*****	**2.68**	**95.14**
Rehearsal	—	—	—	—	—	—	—	—	—
Elaboration	4	3	5,512	.25	−.16	.59	55.30(3)***	5.63	93.12
Organization	—	—	—	—	—	—	—	—	—
Critical thinking	—	—	—	—	—	—	—	—	—
Other	8	2	210	.37	−.45	.85	88.30(7)***	4.49	90.41
Metacognitive strategies	**48**	**5**	**5,545**	**.35***	**.08**	**.57**	**778.39(47)*****	**5.38**	**92.65**
Goal setting and planning	23	3	5,048	.39*	.04	.65	355.19(22)***	12.02	86.31
Self-monitoring	—	—	—	—	—	—	—	—	—
Self-evaluation and reaction	21	4	5,356	.26	−.06	.54	280.12(20)***	1.55	94.92
Self-satisfaction	—	—	—	—	—	—	—	—	—
Metacognitive self-regulation	3	2	359	.55**	.40	.66	1.25(2)	0.00	0.00
Resource management strategies	**13**	**4**	**6,426**	**.20†**	**−.04**	**.41**	**241.40(12)*****	**7.94**	**88.80**
Time and study environment	3	2	1,432	.34*	.02	.60	8.37(2)*	82.07	0.00
Effort regulation	4	2	352	.22	−.48	.75	36.72(3)***	0.00	94.60
Help seeking	4	2	4,994	.02	−.08	.11	11.80(3)**	70.62	0.00
Peer learning	—	—	—	—	—	—	—	—	—
Other	—	—	—	—	—	—	—	—	—
Composite score	**9**	**6**	**7,370**	**.46****	**.26**	**.62**	**601.81(9)*****	**23.61**	**74.76**

Note. Dashes indicate that no meta-analysis was performed due to the limited number of primary studies. SRL = self-regulated learning; *k* = number of effect sizes; *m* = number of primary studies; *n* = total sample size; *r* = average correlation; CI = confidence interval; LL = lower limit. UL = upper limit.
†$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

Table 5-8

Learner Satisfaction: Results for Different Self-Regulated Learning Strategies

SRL strategies	*k*	*m*	*n*	*r*	95% CI of *r*		Heterogeneity		
					LL	UL	*Q*(*df*)	I^2_{within}	$I^2_{between}$
Cognitive strategies [a]	**3**	**3**	**406**	**.26****	**.18**	**.33**	**0.29(2)**	**—**	**0.00**
Rehearsal	—	—	—	—	—	—	—	—	—
Elaboration	—	—	—	—	—	—	—	—	—
Organization	—	—	—	—	—	—	—	—	—
Critical thinking	—	—	—	—	—	—	—	—	—
Other [a]	3	3	406	.26**	.18	.33	0.29(2)	—	0.00
Metacognitive strategies	**19**	**4**	**652**	**.33****	**.15**	**.48**	**55.91(18)*****	**0.00**	**74.78**
Goal setting and planning	7	4	652	.27*	.04	.47	25.28(6)***	74.93	0.00
Self-monitoring	5	3	652	.25**	.12	.36	2.59 (4)	0.00	0.00
Self-evaluation and reaction	6	3	652	.27**	.17	.37	5.12(5)	0.00	0.00
Self-satisfaction	—	—	—	—	—	—	—	—	—
Metacognitive self-regulation	—	—	—	—	—	—	—	—	—
Resource management strategies	**24**	**5**	**581**	**.20*****	**.11**	**.29**	**69.04(23)*****	**69.04**	**0.00**
Time and study environment	9	2	312	.19***	.11	.28	5.28(8)	0.00	0.00
Effort regulation	7	3	475	.09	−.13	.30	12.33(6)†	59.30	0.00
Help seeking	5	3	475	.12	−.20	.41	13.12(4)*	73.01	0.00
Peer learning	—	—	—	—	—	—	—	—	—
Other [a]	3	3	481	.39**	.28	.49	0.80(2)	—	0.00
Composite score	**4**	**3**	**524**	**.27****	**.14**	**.39**	**1.67(3)**	**0.00**	**0.00**

Note. Dashes indicate that no meta-analysis was performed due to the limited number of primary studies; SRL = self-regulated learning. *k* = number of effect sizes; *m* = number of primary studies; *n* = total sample size; *r* = average correlation; CI = confidence interval; LL = lower limit. UL = upper limit.

[a] A traditional two-level meta-analysis (variance components: sampling variance and variance between studies) was performed because only one effect size was reported per study (restricted maximum-likelihood and the Knapp and Hartung, 2003 method were used to compute the models).

$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table 5-9

Organizational Learning Culture: Results for Different Self-Regulated Learning Strategies

SRL strategies	*k*	*m*	*n*	*r*	95% CI of *r*		Heterogeneity		
					LL	UL	*Q*(*df*)	I^2_{within}	$I^2_{between}$
Cognitive strategies	**9**	**4**	**940**	**.15***	**.08**	**.22**	**5.23(8)**	**.00**	**22.60**
Rehearsal	—	—	—	—	—	—	—	—	—
Elaboration	—	—	—	—	—	—	—	—	—
Organization	—	—	—	—	—	—	—	—	—
Critical thinking	—	—	—	—	—	—	—	—	—
Other	8	3	770	.13**	.07	.20	3.49(7)	0.00	12.62
Metacognitive strategies	**12**	**3**	**510**	**.27****	**.10**	**.42**	**41.24(11)***	**32.06**	**45.44**
Goal setting and planning	4	3	510	.22	−.23	.59	29.16(3)***	3.19	86.70
Self-monitoring	—	—	—	—	—	—	—	—	—
Self-evaluation and reaction	—	—	—	—	—	—	—	—	—
Self-satisfaction	—	—	—	—	—	—	—	—	—
Metacognitive self-regulation [a]	2	2	373	.31	−.84	.95	5.39(1)*	—	81.43
Resource management strategies	**13**	**4**	**1,788**	**.23***	**.03**	**.42**	**77.18(12)***	**2.65**	**84.57**
Time and study environment	—	—	—	—	—	—	—	—	—
Effort regulation	4	2	333	.05	−.18	.27	3.34(3)	0.00	47.86
Help seeking	4	2	333	.06	−.30	.40	6.56(3)†	0.00	76.50
Peer learning	—	—	—	—	—	—	—	—	—
Other	4	2	375	.30	−.21	.68	14.72(3)**	0.00	88.09
Composite score	**10**	**6**	**2,274**	**.27***	**.17**	**.37**	**72.89(9)***	**15.87**	**68.54**

Note. Dashes indicate that no meta-analysis was performed due to the limited number of primary studies; SRL = self-regulated learning. *k* = number of effect sizes; *m* = number of primary studies; *n* = total sample size; *r* = average correlation; CI = confidence interval; LL = lower limit. UL = upper limit.

[a] A traditional two-level meta-analysis (variance components: sampling variance and variance between studies) was performed because only one effect size was reported per study (restricted maximum-likelihood and the Knapp and Hartung, 2003 method were used to compute the models).

†*p* < .10. **p* < .05. ***p* < .01. ****p* < .001.

Table 5-10

Regression Coefficients for Moderators and Their 95% Confidence Intervals

SRL strategies	Intercept	Op. SRL strategies [a]	Op. associated factor [a]	Setting [b]	Work-relatedness [c]	Formality [d]
Achievement motivation						
Pooled	.36*** [.21, .49]	−.32*** [−.47, −.14]	—	−.10 [−.26, .05]	−.00 [−.16, .15]	.09 [−.07, .25]
Cognitive strategies	.44* [.10, .69]	—	—	−.18 [−.48, .17]	−.11 [−.43, .22]	−.16 [−.40, .09]
Metacognitive strategies	.43*** [.30, .55]	−.39*** [−.49, −.27]	—	−.13* [−.25, −.01]	−.05 [−.18, .08]	−.03 [−.20, .14]
Resource management strategies	.19** [.06, .33]	−.18† [−.38, .02]	—	−.08 [−.21, .04]	.14* [.01, .26]	.13 [−.08, .33]
Composite score	.50** [.20, .71]	—	—	−.17 [−.49, .19]	−.11 [−.45, .24]	.05 [−.35, .43]
Learning performance						
Pooled	.44† [−.01, .74]	−.18 [−.68, .43]	−.06 [−.26, .14]	−.30 [−.70, .25]	.35 [−.11, .68]	.27 [−.08, .55]
Cognitive strategies	.12 [−.12, .36]	—	−.00 [−.30, .30]	−.03 [−.50, .44]	—	.07 [−.21, .34]
Metacognitive strategies	.31 [−.20, .69]	.05 [−.54, .60]	—	—	—	.26 [−.33, .70]
Resource management strategies	.39 [−.19, .76]	.10 [−.56, .68]	−.02 [−.25, .22]	−.36 [−.81, .34]	—	.26 [−.26, .67]
Composite score	.62*** [.41, .77]	—	—	−.32† [−.61, .04]	—	—
Learner engagement						
Pooled	.24 [−.54, .80]	.22 [−.50, .76]	−.08 [−.19, .03]	.07 [−.61, .69]	.01 [−.59, .60]	.25 [−.41, .74]
Cognitive strategies	.55 [−.64, .96]	.20 [−.72, .87]	−.08** [−.13, −.03]	−.35 [−.95, .81]	−.48 [−.93, .54]	—
Metacognitive strategies	.38 [−.69, .93]	.14 [−.77, .87]	−.08 [−.19, .02]	.27 [−.71, .90]	−.26 [−.82, .55]	—
Resource management strategies	.19 [−.22, .54]	—	—	—	.01 [−.52, .53]	—
Composite score of SRL strategies	.25 [−.55, .81]	—	—	.29 [−.47, .80]	.07 [−.59, .67]	—
Learner satisfaction						
Pooled	.33* [.02, .59]	−.37* [−.61, −.06]	—	.03 [−.32, .38]	−.04 [−.44, .37]	—
Cognitive strategies	—	—	—	—	—	—
Metacognitive strategies	.31* [.02, .55]	−.44** [−.66, −.15]	—	.12 [−.29, .49]	—	—
Resource management strategies	.36† [−.06, .67]	−.34* [−.56, −.07]	—	−.04 [−.51, .45]	−.15 [−.58, .35]	—
Composite score	—	—	—	—	—	—
Organizational learning culture						
Pooled	.25** [.16, .34]	—	—	—	—	−.00 [−.00, .00]
Cognitive strategies	.17** [.06, .28]	—	—	—	—	−.04 [−.19, .11]
Metacognitive strategies	—	—	—	—	—	—
Resource management strategies	—	—	—	—	—	—
Composite score	—	—	—	—	—	—

Note. Regression coefficients indicate the difference in *r* between the category coded with 1 and its reference category. Dashes indicate that moderator analyses were not performed due to limited variance of moderator variables. Studies that did not report sufficient information on moderators were dropped from analyses. SRL = self-regulated learning; Op. = operationalization.

[a] 0 = subjective, 1 = objective. [b] 0 = online, 1 = face-to-face. [c] 0 = work-related, 1 = non-work-related. [d] 0 = formal/non-formal, 1 = informal.

†$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

Table 5-11

Omnibus Tests of Moderators and Residual Heterogeneity Not Explained by Moderators

SRL strategies	Omnibus test	Residual heterogeneity		
	$F(df1, df2)$	$Q(df)$	I^2_{within}	$I^2_{between}$
Achievement motivation				
Pooled ($k = 180$, $m = 22$)	3.41(4, 175)*	1,224.29(175)***	56.65	30.70
Cognitive strategies ($k = 42$, $m = 12$)	1.18(3, 38)	333.88(38)***	43.11	46.59
Metacognitive strategies ($k = 75$, $m = 14$)	9.35(4, 70)***	288.83(70)***	67.26	10.42
Resource management strategies ($k = 80$, $m = 13$)	3.29(4, 75)*	422.23(75)***	69.54	14.31
Composite score ($k = 21$, $m = 11$)	0.43(3, 17)	252.14(17)***	43.82	47.71
Learning performance				
Pooled ($k = 61$, $m = 15$)	1.33(5, 55)	1,075.90(55)***	34.89	62.18
Cognitive strategies ($k = 19$, $m = 7$)	0.24(2, 16)	199.46(16)***	81.94	8.98
Metacognitive strategies ($k = 18$, $m = 6$)	0.66(2, 15)	328.99(15)***	19.68	75.43
Resource management strategies ($k = 31$, $m = 9$)	0.87(4, 26)	435.72(26)***	25.20	72.22
Composite score ($k = 8$, $m = 5$)	4.67(1, 6)†	52.17(6)***	16.96	73.48
Learner engagement				
Pooled ($k = 71$, $m = 10$)	0.73(5, 65)	699.08(65)***	6.81	92.08
Cognitive strategies ($k = 13$, m =5)	3.50(4, 8)†	49.94(8)***	0.00	98.22
Metacognitive strategies ($k = 48$, $m = 5$)	0.94(4, 43)	191.03(43)***	1.92	97.02
Resource management strategies ($k = 13$, $m = 4$)	0.00(1, 11)	187.76(11)***	5.42	92.36
Composite score ($k = 10$, $m = 7$)	0.58(2, 7)	302.85(7)***	23.34	76.22
Learner satisfaction				
Pooled ($k = 29$, $m = 7$)	3.03(3, 25)*	62.43(25)***	6.76	62.93
Cognitive strategies ($k = 3$, m =3)	—	—	—	—
Metacognitive strategies ($k = 19$, $m = 4$)	5.49(2, 16)*	30.79(16)**	0.00	7.75
Resource management strategies ($k = 24$, $m = 5$)	2.82(3, 20)†	47.26(20)***	23.32	53.44
Composite score ($k = 4$, $m = 3$)	—	—	—	—
Organizational learning culture				
Pooled ($k = 39$, $m = 10$)	0.10(1, 37)	240.93(37)***	12.24	73.13
Cognitive strategies ($k = 9$, m =4)	0.35(1, 7)	3.98(7)	0.00	26.85
Metacognitive strategies ($k = 19$, $m = 4$)	—	—	—	—
Resource management strategies ($k = 24$, $m = 5$)	—	—	—	—
Composite score ($k = 4$, $m = 3$)	—	—	—	—

Note. Dashes indicate that moderator analyses were not performed due to limited variance of moderator variables. Studies that did not report sufficient information on moderators were dropped from analyses. SRL = self-regulated learning; k = number of effect sizes; m = number of primary studies.
†$p < .10$. *$p < .05$. ***$p < .001$.

5.8 Discussion

SRL strategies have been considered key competences for CE (Haemer et al., 2017; Kittel et al., 2021). Our systematic review and meta-analysis investigated factors associated with learners' use of SRL strategies in CE. Several learning process-related (e.g., achievement motivation), learner-related (e.g., prior knowledge), CE-related (e.g., peer interaction), and work-related (e.g., organizational learning culture) factors associated with SRL strategies in CE were identified. Operationalization of variables as well as setting and work-relatedness of the CE activity were identified as moderators.

5.8.1 Interpretation of Results and Theoretical Implications

Learning Process-Related Factors

While previous systematic reviews and meta-analyses have identified relationships between SRL strategies and achievement motivation, learning performance, and goal achievement (Lee et al., 2019; Sitzmann & Ely, 2011), our systematic review and meta-analysis detected several additional learning process-related factors associated with SRL strategies in CE. For example, our meta-analysis revealed significant positive relationships between SRL strategies and learner engagement as well as learner satisfaction.

Our meta-analysis is the first meta-analysis to focus on the relationships between SRL strategies and different learning process-related factors in different types of CE. Previous meta-analyses have mainly concentrated on the relationships between SRL strategies and learning performance in K-12 (e.g., J. Li et al., 2018) and higher education (e.g., Broadbent & Poon, 2015). The average correlations between SRL strategies and learning performance in our meta-analysis (e.g., r = .36 for the pooled meta-analysis) tend to be higher than in previous meta-analyses focusing on K-12 (e.g., r = .18 in J. Li et al., 2018) and higher education (e.g., r = .13 in Broadbent & Poon, 2015). Although this interpretation should be treated with caution, as our meta-analysis is based on correlations, our findings suggest that the need for SRL strategies in CE might be even greater than in K-12 and higher education. Especially, metacognitive and resource management strategies seem to play an important role for learning performance in CE, as average correlations for these strategies indicated stronger relationships than for cognitive strategies. Whereas learning is the main task of K-12 and full-time higher education students, our systematic review indicates that learners in CE have to balance learning with professional and family commitments, limiting the time they have available for learning (Hosseini et al., 2020; Rabin et al., 2020). Therefore, learners' ability to efficiently plan, monitor, and evaluate their learning processes, as well as effective time management and effort regulation strategies, might be more crucial in CE than in K-12 and higher education (Milligan & Littlejohn, 2016; Vanslambrouck, Zhu, Pynoo, Thomas, et al., 2019). In our meta-analysis, the relationships between some specific metacognitive (e.g., self-monitoring) and resource management (e.g., effort regulation) strategies and learning performance were not significant. We suggest that this lack of significance might be due to low statistical power resulting from the small number of included effect sizes and primary studies, as average correlation coefficients indicated strong effects, according to Cohen (1988).

Learner-Related Factors

Previous systematic reviews have identified learner-related factors (e.g., cognitive ability, prior knowledge) associated with SRL strategies (van Houten-Schat et al., 2018; J. Wong et al., 2019). However, these systematic reviews did not focus on CE exclusively and included studies focusing on higher education. Our systematic review and meta-analysis are the first to focus on learner-related factors associated with SRL strategies in CE. While some of the learner-related factors identified in our investigations (e.g., gender, prior knowledge, CE experience) are similar to those identified in previous systematic reviews (van Houten-Schat et al., 2018; J. Wong et al., 2019), other factors from previous systematic reviews (e.g., cognitive ability; J. Wong et al., 2019) could not be replicated and might be more relevant in higher education.

The findings of our meta-analysis suggest that learner-related factors may be less relevant for SRL in CE than learning process-related and work-related factors, as only weak and partially nonsignificant relationships between SRL strategies and the learner-related factors studied in our pooled meta-analyses were revealed. However, our systematic review identified several learner-related factors (e.g., curiosity, general self-regulation) for which meta-analyses were not conducted because information on effect sizes was not sufficient. Thus, the strengths of the relationships between SRL strategies and these learner-related factors still remain unclear.

Continuing Education-Related Factors

Our investigations complement the list of CE-related factors associated with SRL strategies in previous systematic reviews focusing on MOOCs and online higher education (e.g., Alonso-Mencía et al., 2020; J. Wong et al., 2019). Our findings suggest that specific instructional methods may trigger specific SRL strategies. For example, opportunities for peer interaction (e.g., discussion forums) may trigger peer learning (Janakiraman et al., 2018). Self-assessments may trigger self-evaluation and reaction (Littlejohn, Hood, et al., 2016). According to qualitative studies included in our investigations, SRL strategies are especially important to deal with learner autonomy in online learning environments (Milligan & Littlejohn, 2016; Vanslambrouck, Zhu, Pynoo, Thomas, et al., 2019) and to persist in CE activities with a long duration (Janakiraman et al., 2018). Moreover, our findings suggest that quality indicators of the CE activity are associated with SRL strategies. For example, ease of use may be an antecedent and outcome of SRL strategies: A learning environment that is easy to use may help learners engage in SRL strategies. In turn, SRL strategies may help learners interact within the learning environment easily (An et al., 2024; Lin et al., 2018).

Work-Related Factors

Our systematic review and meta-analysis provide the first comprehensive list of work-related variables associated with SRL strategies in CE. Our findings suggest that a positive organizational learning culture may motivate learners to use SRL strategies (Kittel et al., 2021). Further, high job control and job demands may empower learners to engage in active learning behavior (Karasek, 1979; Raemdonck et al., 2014), while increasing the need for effective SRL strategies (Gijbels et al., 2012). In our meta-analysis, the relationship between SRL strategies and organizational learning culture was stronger for metacognitive than for cognitive and resource management strategies. Although no statements about causality can be made, this might indicate that a positive organizational learning culture may particularly motivate learners to plan, monitor, and evaluate their work-related learning activities (Kittel et al., 2021; Lin et al., 2018). Moreover, learners' successful engagement in metacognitive strategies might help recognize work-related learning opportunities, increase learners' satisfaction with their work-related learning behavior, and, in turn, positively impact learners' perceptions of the organizational learning culture (Lin et al., 2018; Zimmerman & Schunk, 2007). Our meta-analyses for the relationships between goal setting and planning as well as metacognitive self-regulation and organizational learning culture were not significant. Again, we suggest that this may be due to low statistical power, as average correlation coefficients indicated a weak to moderate effect for goal setting and planning and a moderate effect for metacognitive self-regulation, according to Cohen (1988).

Moderators

According to our moderator analyses, the relationship between SRL strategies and achievement motivation, as well as the relationship between SRL strategies and learner satisfaction, tends to be stronger for subjective measures of SRL strategies than for objective measures. Moreover, the relationship between cognitive strategies and learner engagement tends to be stronger for subjective measures of learner engagement than for objective measures. These findings might indicate that subjective and objective measures of SRL strategies and learner engagement do not measure the same overall construct. Measuring SRL strategies and learner engagement using behavioral measures, particularly trace data in online learning environments, has become a popular technique (Kizilcec et al., 2017; Saint et al., 2020). However, research has shown that trace data do not always calibrate to self-report questionnaires (Hadwin et al., 2007; van Halema et al., 2020). Moreover, our findings suggest that the relationships between SRL strategies and achievement motivation as well as learner satisfaction are stronger if the operationalization of SRL strategies matches the operationalization of the associated factors. In all included primary studies, achievement motivation and learner satisfaction were measured subjectively using self-report questionnaires. Therefore, their association with SRL strategies may be stronger if SRL strategies are also measured subjectively and reflect learners' individual perceptions (Spector & Brannick, 2009).

Moreover, our moderator analyses identified the setting of the CE activity as a significant moderator of the relationship between metacognitive strategies and achievement motivation, with a stronger relationship for CE activities delivered completely online than for CE activities including face-to-face sessions. As suggested in qualitative studies identified in our systematic review, this might be due to the higher degrees of learner autonomy and flexibility associated with online learning (Milligan & Littlejohn, 2016; Vanslambrouck, Zhu, Pynoo, Thomas, et al., 2019). In face-to-face settings, instructors may provide external regulation and help learners set appropriate learning goals as well as plan, monitor, and adjust their learning behaviors. In online settings, instructors are less present, and the need for metacognitive strategies to self-regulate learning processes is higher (Broadbent & Poon, 2015; Milligan & Littlejohn, 2016; Nawrot & Doucet, 2014).

According to our moderator analyses, the relationship between resource management strategies and achievement motivation tends to be stronger for non-work-related CE than for work-related CE. Motivational beliefs in work-related CE may be externally regulated by the employer. For example, participation in work-related CE may be mandatory, and learners may need to adhere to specific deadlines set by the employer (Hemmler et al., 2023). In contrast, participation in non-work-related CE is less externally regulated, and learners are required to apply resource management strategies to regulate their internal and external resources (Demary et al., 2013; Hemmler et al., 2023; Nawrot & Doucet, 2014).

None of the analyses conducted for the moderator formality of the CE activity were significant. We conclude that the factors associated with SRL strategies in CE do not differ for formal/non-formal and informal CE. This is consistent with some previous works (e.g., Kittel et al., 2021; Lee et al., 2020a) suggesting that the major assumptions of SRL theories equally apply to formal, non-formal, and informal CE. However, the non-significance of the moderator analyses for formality might also be due to low statistical power, as some of the regression coefficients showed weak to moderate effects.

5.8.2 Limitations and Implications for Future Research

Our work is subject to limitations that provide implications for future research. First, our findings might be biased because we only considered studies published in English and in peer-reviewed journals. When conducting systematic reviews and meta-analyses, researchers face the dilemma of choosing between bias due to low-quality primary studies and publication bias. To guarantee a minimum level of quality and to avoid the garbage-in-garbage-out problem, we decided to include studies published in peer-reviewed journals only (Egger et al., 2001). This might have increased publication bias, as unpublished and informally published studies were not considered (Borenstein et al., 2009). The three-level version of the Egger's regression test (Fernández-Castilla et al., 2021; Rodgers & Pustejovsky, 2021) revealed no statistically significant asymmetry in funnel plots for our pooled meta-analyses, suggesting no publication bias. However, reliable methods for detecting publication bias in three-level meta-analyses are still lacking, and research has shown that the three-level version of the Egger's regression test may suffer from a lack of statistical power (Rodgers & Pustejovsky, 2021). Therefore, the results of the three-level version of the Egger's regression test need to be interpreted with caution, and future research should include a more comprehensive search of publications.

Second, our meta-analytic results indicate heterogeneity in effect sizes, which could not be fully explained by our moderators. Therefore, more research on moderators is needed. The learning process-related, learner-related, CE-related, and work-related factors identified in our investigations may serve as a starting point for future moderator analyses, as research has suggested that these factors may interact with each other (Lin et al., 2018; Zimmerman & Schunk, 2007).

Third, our meta-analysis is based on correlational findings, and no statements about causality can be made. Our findings do not allow us to draw any conclusions about whether the factors investigated in our meta-analysis represent antecedents or outcomes of SRL strategies. Therefore, future research and meta-analyses should focus on experimental studies investigating SRL strategies in CE.

5.8.3 Practical Implications

Our findings help understand the nature of SRL in CE and provide a sound basis for designing interventions to support SRL. Although this implication should be considered with caution, as no statements about causality can be made, our meta-analysis provides first indications that supporting learners' use of SRL strategies might be beneficial to enhance achievement motivation, learning performance, learner engagement, and learner satisfaction in CE.

J. Wong et al. (2021) and Jansen et al. (2020) designed and evaluated interventions aiming to support SRL in CE. These interventions consisted of a writing activity where learners should reflect on their learning goals as well as explanation videos on SRL strategies. However, these interventions had limited effects on SRL strategies, and in Jansen et al.'s (2020) study, several learners did not actively engage with the intervention. Since time is a rare commodity in CE (Eriksson et al., 2017; Hosseini et al., 2020), we suggest that the interventions designed by J. Wong et al. (2021) and Jansen et al. (2020) might have required too much time and effort in addition to learning activities.

Whereas interventions to support SRL may be beneficial in different types of CE, they might be particularly important in online and non-work-related CE, according to our moderator analyses. Regarding online CE, the increasing use of digitally supported learning environments offers new opportunities for supporting SRL through learning analytics (Araka et al., 2020; Schumacher & Ifenthaler, 2018). Learning analytics refer to the use of static and dynamic data about learners and learning environments, for real-time modeling, analysis, prediction, and support of learning processes (Ifenthaler, 2015; Ifenthaler & Yau, 2020; B. T.-M. Wong & Li, 2020). When learners interact in digitally supported learning environments, vast amounts of education-related data can be collected, providing useful insights into learning behavior and SRL processes that might be used to design personalized interventions (Pérez-Álvarez et al., 2020; Schumacher & Ifenthaler, 2018). For example, trace data can be analyzed to draw inferences about how learners self-regulate and can be provided to learners in the form of personalized dashboards (Pérez-Álvarez et al., 2020; Matcha et al., 2020). Such interventions may support SRL strategies without requiring learners to spend much additional time and effort on SRL interventions (Nawrot & Doucet, 2014; Pérez-Álvarez et al., 2020). However, to effectively support SRL in CE through learning analytics, learning analytics need to be more firmly grounded in SRL theory, and valid frameworks for measuring SRL strategies through trace data need to be developed (Giannakos & Cukurova, 2023; Marzouk et al., 2016).

Finally, our findings have implications for work organizations by suggesting that work-related factors are associated with SRL strategies in CE. Work organizations should create an organizational learning culture supporting employees' engagement in CE activities as well as a challenging work environment supporting employees' autonomy and control over their work tasks (Gijbels et al., 2012; Kittel et al., 2021; Raemdonck et al., 2014). Although these interpretations are based on correlative findings and should be treated with caution, work organizations may play a relevant role in learners' motivation and ability to engage in SRL strategies (Gijbels et al., 2012; Kittel et al., 2021). In this regard, organizations may allow employees to spend a certain amount of their working time on CE activities, as CE often clashes with professional commitments (Vanslambrouck, Zhu, Pynoo, Thomas, et al., 2019).

5.8.4 Conclusion

Due to the fast-paced nature of today's (working) world, individuals are constantly required to participate in CE activities and to engage in SRL processes (Kittel et al., 2021; Manuti et al., 2015; Nawrot & Doucet, 2014). Our systematic review and meta-analysis identified learning process-related, learner-related, CE-related, and work-related factors associated with SRL strategies in CE, as well as variables moderating the underlying relationships. Our investigations help understand the nature of SRL in CE and provide a sound basis for designing interventions to support SRL in CE.

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6. Paper 4: Personalization Is No Miracle Cure: Evaluation of a Technology-Enhanced Self-Regulated Learning Intervention for Continuing Education

6.1 Introduction

Continuing education (CE) is a central element of lifelong learning and essential for keeping up-to-date in today’s rapidly changing society and workforce landscape (Mlambo et al., 2021; Omar et al., 2024). 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 (Demary et al., 2013; *Further and Higher Education Act*, 1992; Schiersmann, 2007). To successfully participate in CE activities, learners need to engage in self-regulated learning (SRL) to regulate their cognitions, affects, behaviors, and resources (Hemmler & Ifenthaler, 2024; D. Lee et al., 2019; Zimmerman & Schunk, 2011). 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 (Fontana et al., 2015; Zimmerman, 2000). 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 (Guntur & Purnomo, 2024; Hemmler & Ifenthaler, 2024).

However, many learners in CE struggle to successfully engage in SRL, which may lead to dropouts and poor learning performance (Chen & Jang, 2019; Eriksson et al., 2017; Nawrot & Doucet, 2014). Therefore, researchers have begun to develop interventions to support SRL in CE (Dinh & Phuong, 2024; Wong et al., 2019). 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 (Heikkinen et al., 2023; Matcha et al., 2020; Teich et al., 2024). However, robust empirical evidence regarding the effectiveness of TEPSIs in supporting learning processes in CE is missing. For example, there are only a few experimental studies evaluating TEPSIs in the context of CE, and these studies have shown limited effects on learning outcomes and SRL (D. Davis et al., 2016;

Psathas et al., 2023; Teich et al., 2024). Moreover, studies have shown that learners in CE do not actively engage with TEPSIs (Cobos, 2023; Teich et al., 2024). For example, in Cobos's (2023) study, a monthly average of only 6% of the learners in a Massive Open Online Course (MOOC) interacted with a TEPSI consisting of 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 (González-Castro et al., 2021; Park et al., 2023). For example, learners' perceived ease of use and usefulness of TEPSIs should be explored to identify potential benefits and weaknesses from the users' perspective (González-Castro et al., 2021; Granić & Marangunić, 2019; Khosravi et al., 2020).

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 are accepted and actively used by learners in CE (González-Castro et al., 2021; Khosravi et al., 2020; Park et al., 2023). 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 interview study using the think-aloud method (Study 2) to investigate learners' perceived ease of use and usefulness of the TEPSI.

6.2 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 reach personal learning goals (Pintrich, 2000; Zimmerman & Schunk, 2011). SRL involves the use of SRL strategies, including cognitive, metacognitive, and resource management strategies (Pintrich et al., 1991, 1993; Winne, 2011, 2022; Zimmerman & Pons, 1986). Cognitive strategies (e.g., rehearsal, elaboration) refer to processing information from learning materials (Pintrich et al., 1991, 1993; Wild & Schiefele, 1994; Winne, 2011). Metacognitive strategies (e.g., goal setting and planning, self-monitoring) help learners plan, monitor, and control their cognitions and application of cognitive strategies (Pintrich et al., 1991, 1993; Theobald, 2021). 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 (Pintrich, 1999; Pintrich et al., 1991, 1993; Theobald, 2021; Wild & Schiefele, 1994).

Although SRL strategies have been considered a critical aspect for learning success in CE (Hemmler & Ifenthaler, 2024; D. Lee et al., 2019), SRL theories (e.g., Pintrich, 2000; Zimmerman, 2000) typically focus on K-12 and higher education and neglect the unique nature of SRL in CE (Cuyvers et al., 2020; Panadero, 2017). 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 cause distractions. While learning is the main occupation of K-12 and full-time higher education students, CE usually takes place alongside the learners' main occupation (e.g., work) and may be less prioritized than concurrent commitments (Eriksson et al., 2017; Schröer et al., 2022; Teich et al., 2024). Moreover, learners in CE are usually characterized by a stronger need for self-direction than learners in K-12 and higher education (Knowles, 1985; Knowles et al., 2012; Manning, 2007) and are often given a higher degree of autonomy to decide when, how, and what they would like to learn (Sitzmann & Ely, 2011). Therefore, the factors triggering learners' use of SRL strategies and the relevance of specific SRL strategies differ between CE and K-12 as well as higher education (Hemmler & Ifenthaler, 2024).

According to Hemmler and Ifenthaler's (2024) 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 (2024) 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 (Sitzmann & Ely, 2011; Teich et al., 2024). 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 (Kizilcec et al., 2017; Nguyen et al., 2024), creating a feasible learning plan (Nguyen et al., 2024; Onah et al., 2024), monitoring their learning progress (Nguyen et al., 2024), evaluating their learning performance objectively (Nguyen et al., 2024), and adapting their learning behavior to improve performance (Milligan & Littlejohn, 2016; Nguyen et al., 2024). 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 (Nawrot & Doucet, 2014; Pintrich et al., 1991; Teich et al., 2024). In particular, time management has been considered essential for CE due to scheduling conflicts (da Luz et al., 2018; Nawrot & Doucet, 2014; Schröer et al., 2022). In their systematic review and meta-analysis, Hemmler and Ifenthaler (2024) 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 (Hosseini et al., 2020; Milligan & Littlejohn, 2016; Rabin et al., 2020). Accordingly, lack of time and ineffective time management have been identified as common reasons for dropout from CE (da Luz et al., 2018; Eriksson et al., 2017; Nawrot & Doucet, 2014; Wang et al., 2023).

6.3 Supporting Self-Regulated Learning in Continuing Education

Since lack of time is a common challenge in CE (Eriksson et al., 2017; Wang et al., 2023), 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 (Khiat, 2022; Teich et al., 2024). 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 (Jansen et al., 2020; Vilkova, 2022; Wong et al., 2021). Moreover, researchers have argued that SRL in CE requires personalized support (Nguyen et al., 2024; Teich et al., 2024), as learners in CE are distinguished by their unique life experiences and diverse preconditions (Knowles et al., 2012; Meister & Willyerd, 2021). For example, learners may enter a CE activity with different expectations, time resources, and levels of prior knowledge, which may impact SRL (Fromm & Ifenthaler, 2024; Hemmler & Ifenthaler, 2024; Winne, 2022).

Hence, researchers have employed educational technologies to develop TEPSIs for CE, such as personalized dashboards (e.g., Cobos, 2023; Pérez-Álvarez et al., 2020; Psathas et al., 2023), personalized prompts (Khiat, 2022; Psathas et al., 2023), and personalized recommendations of learning content (Siadaty et al., 2016; Teich et al., 2024), learning times (Teich et al., 2024), and learning partners (Milikić et al., 2020). For example, Cobos (2023) and Pérez-Álvarez et al. (2020) developed personalized dashboards to support SRL in MOOCs by providing visualizations of individual learning behavior and comparisons with other learners. Further, Psathas et al. (2023) 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. (2024) 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 (2022) 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., Jansen et al., 2020) and written reflection tasks (e.g., Vilkova, 2022), TEPSIs may provide tailored support during the individual learning process and require less time and effort in addition to learning activities (Nguyen et al., 2024; Teich et al., 2024).

Nevertheless, although researchers have emphasized the potential of TEPSIs (Nguyen et al., 2024; Prasse et al., 2024), 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 (Heikkinen et al., 2023; Prasse et al., 2024; Matcha et al., 2020; Viberg et al., 2020). 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 in CE, and the empirical evidence from these studies is limited (D. Davis et al., 2016; Khiat, 2022; Psathas et al., 2023; Teich et al., 2024). For example, the introduced TEPSIs showed negligible effects on SRL (e.g., Psathas et al., 2023), addressed only isolated SRL strategies (e.g., Khiat, 2022), were not actively used by learners (e.g., Teich et al., 2024), 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., Khiat, 2022). Thus, further experimental studies evaluating the effects of TEPSIs on learning outcomes and SRL in CE are needed. Moreover, to address the limited effects of existing TEPSIs and learners' limited engagement with them, robust insights into how learners interact with specific features of TEPSIs 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 (Park et al., 2023; Topali et al., 2025). 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 (F. D. Davis, 1986; Granić, 2022; Granić & Marangunić, 2019). 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 (F. D. Davis, 1986; Granić & Marangunić, 2019; Venkatesh & Davis, 1996).

Perceived usefulness refers to a person's evaluation of the utility of a system for enhancing performance within a particular context of use (F. D. Davis, 1986; Rets et al., 2021; Tran & Ma, 2024). Both perceived ease of use and perceived usefulness have been considered important predictors of learners' intention to use and engage with pedagogical interventions (Granić, 2022; Granić & Marangunić, 2019; Sprenger & Schwaninger, 2021). However, comprehensive studies investigating learners' perceived ease of use and usefulness of TEPSIs in CE are missing.

6.4 The Technology-Enhanced Personalized Self-Regulated Learning Intervention of the edyoucated-Platform

6.4.1 The edyoucated-Platform

We evaluated the TEPSI of the edyoucated-platform (https://edyoucated.org/). The edyoucated-platform, described in detail by Rasch and Middelbeck (2022), 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 Figure 6-1).

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 with increasing prior knowledge, 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 Figure 6-2). 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 (2022) and Fromm et al. (2025).

Figure 6-1

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

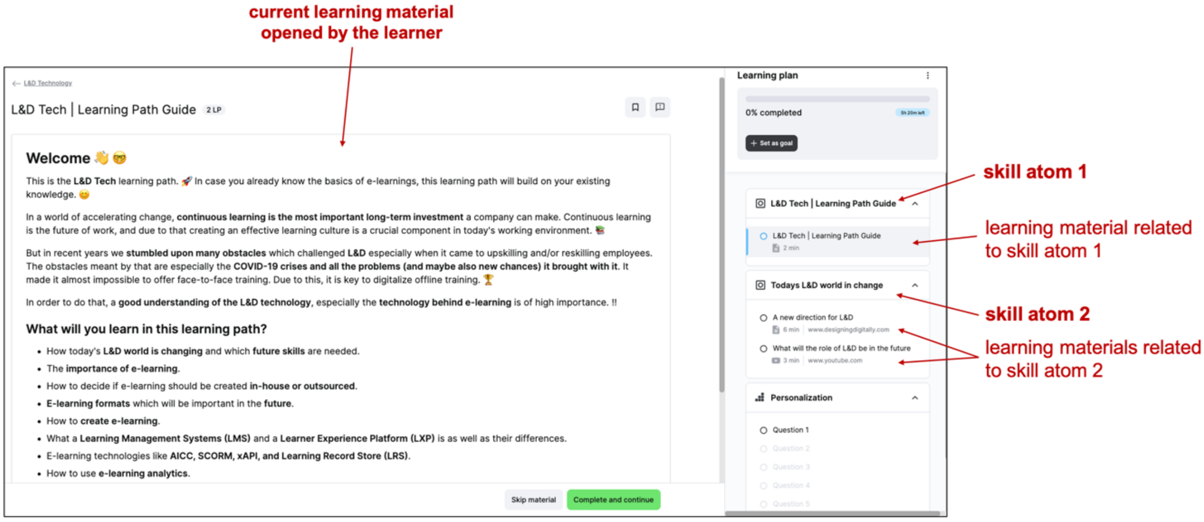
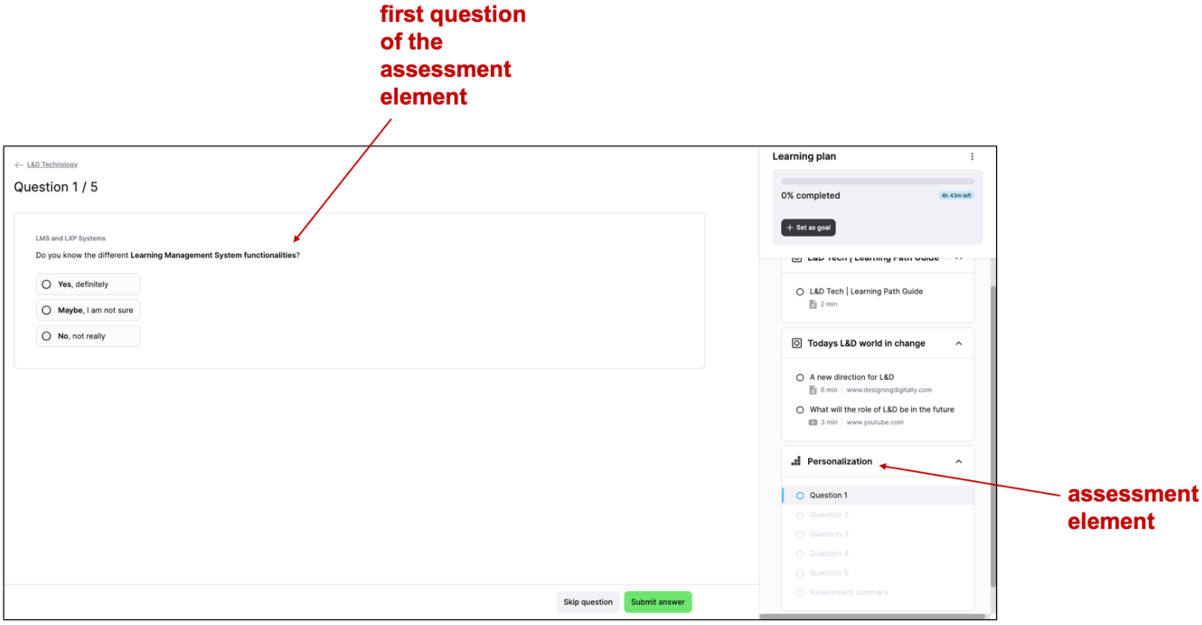


Figure 6-2

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, the assessment of learners' prior knowledge is performed 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 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 (Fromm & Ifenthaler, 2024; Gharahighehi et al., 2024). A recent study revealed positive effects of the learning path personalization system of the edyoucated-platform on knowledge increase in CE (Fromm et al., 2025). 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 (Alshammari et al., 2015; An et al., 2024). 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 personalized learning paths.

6.4.2 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., Hemmler & Ifenthaler, 2024; Nguyen et al., 2024). 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 (Hemmler & Ifenthaler, 2024). Moreover, since the importance of metacognitive and resource management strategies has been emphasized for CE (Alonso-Mencía et al., 2020; Hemmler & Ifenthaler, 2024; Teich et al., 2024) and since learners in CE tend to struggle with these strategies (Nguyen et al., 2024; Onah et al., 2024), the TEPSI of the edyoucated-platform focuses on supporting metacognitive and resource management strategies. Nguyen et al. (2024) 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 to set learning goals and create a learning plan, by providing visualizations that enable learners to track their progress toward their goals, and by offering recommendations for improving learning behavior. Further, according to Nguyen et al. (2024), resource management strategies may be supported by providing information on required learning time, by breaking down overall learning goals into smaller steps, 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 Figure 6-3). 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 needed to complete the learning path until the deadline is displayed when learners select a specific date (see Figure 6-4). 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 in 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.

Figure 6-3

Accessing the Goal-Setting Functionality

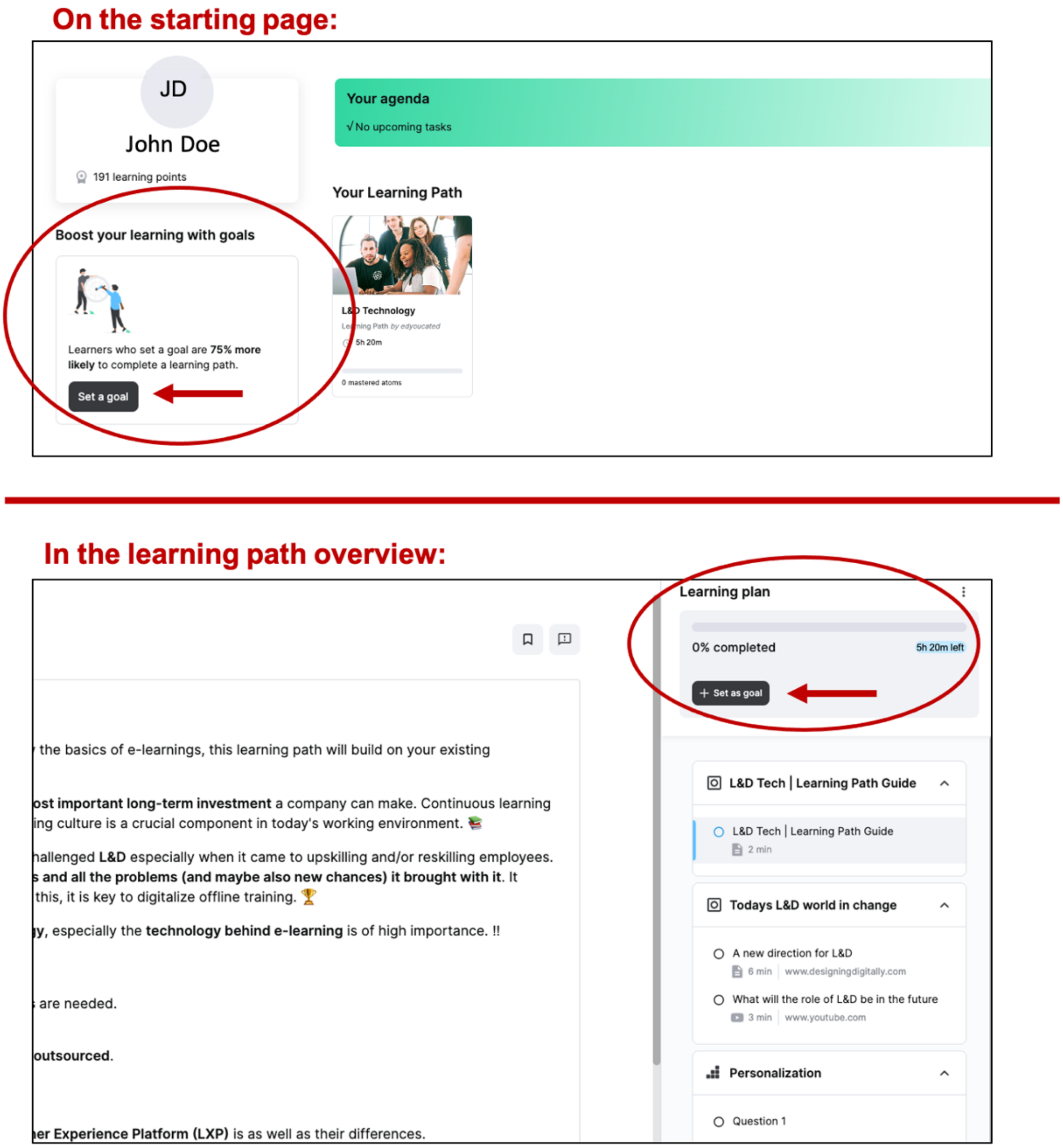
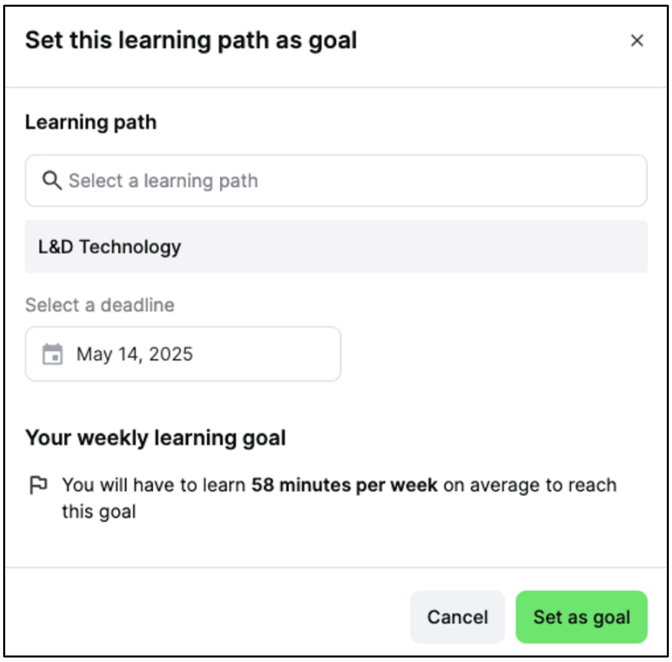


Figure 6-4

Setting an Overall Learning Goal



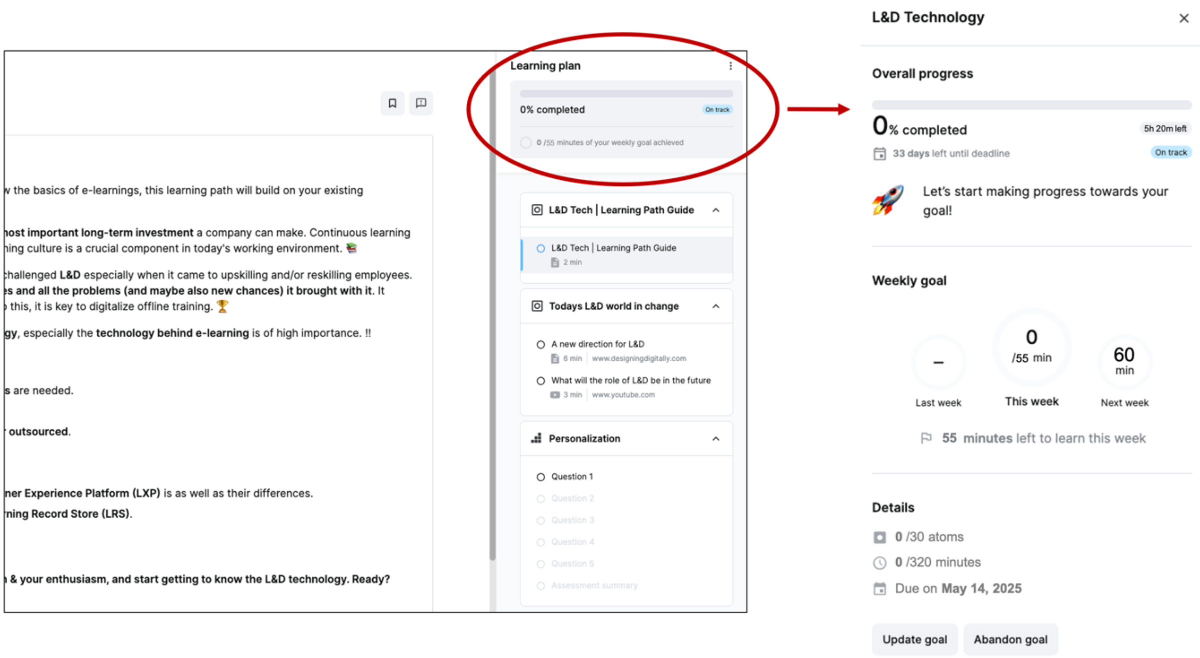
In the learning path overview, learners can open a personalized dashboard to access their personalized learning plan and monitor their individual goal progress (see Figure 6-5). The personalized dashboard consists of three parts: overall progress, weekly goal, and details. Figure 6-6 shows different possible states of the personalized dashboard. The overall progress part visualizes learners' progress toward their overall learning goal. It provides personalized feedback consisting of a timely progress indicator (on track, at risk, overdue, or completed) and a short 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 different learning materials within a learning path differ in their duration, the weekly goals may differ between the weeks and fluctuate around the average weekly learning time. Moreover, in the TEPSI, a week is defined to start on Monday and to end 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 6-1 provides a detailed overview of how the TEPSI of the edyoucated-platform addresses specific SRL strategies.

Figure 6-5

Accessing the Personalized Dashboard



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

Figure 6-6

Possible States of the Personalized Dashboard

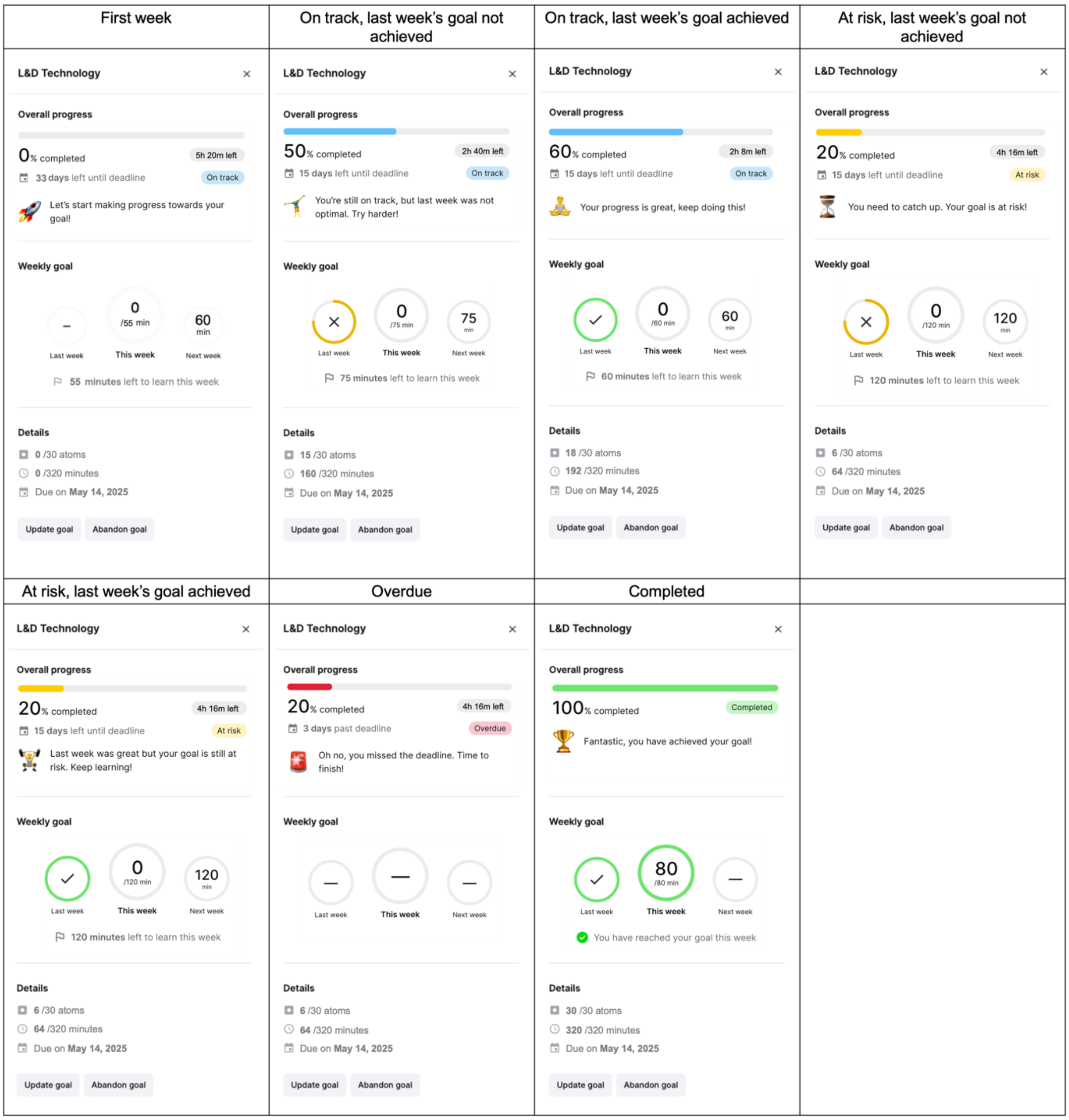


Table 6-1

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 (Theobald, 2021; Zimmerman & Pons, 1986)	• 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 (Theobald, 2021)	• 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 (Pintrich et al., 1991, 1993; Theobald, 2021)	• 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 (Pintrich et al., 1991, 1993)	• 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 (Pintrich et al., 1991, 1993)	• 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.

6.5 Research Questions

To evaluate the TEPSI of the edyoucated-platform, the following research questions were answered by the two studies of this paper:

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

6.6 Study 1

6.6.1 Method

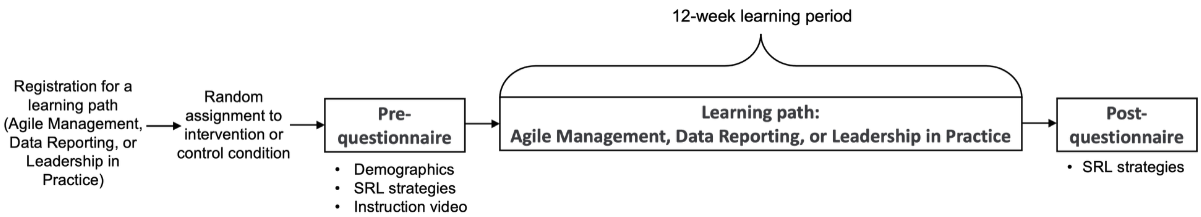
Research Design and Procedure

To answer Research Question 1 and Research Question 2, 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 6.4.2 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 ~ 5.5 hours), Data Reporting (~ 6.5 hours), or Leadership in Practice (~ 10 hours). All three learning paths included learning materials in the form of videos, texts, and short quizzes. A detailed overview of the learning paths is presented in Appendix D. 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 Figure 6-7. 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 (~ 3 minutes) whose content differed between the two experimental conditions. The instruction video of 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.

Figure 6-7

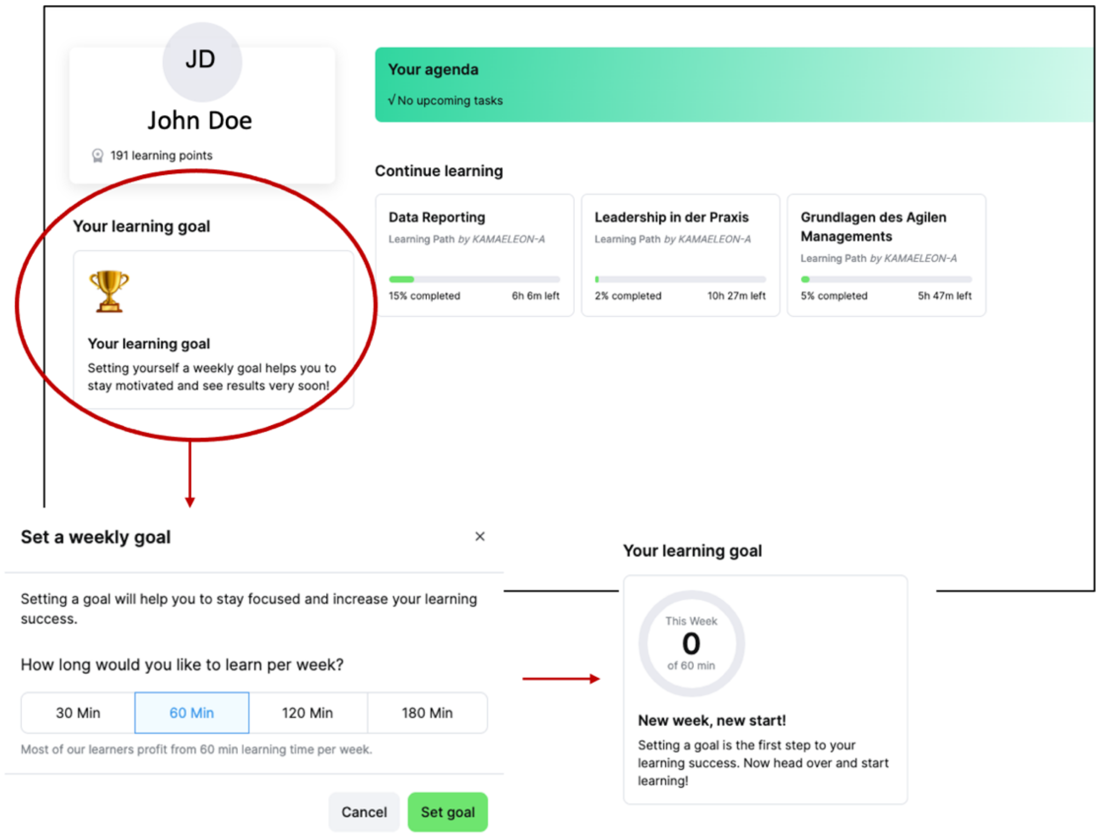
Overview of the Study Procedure (Study 1)



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 Figure 6-8). 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 Figure 6-9). These features provided in the control condition refer to typical features of online learning platforms, such as edX (https://www.edx.org/) and Udemy (https://www.udemy.com/), and, therefore, provide a realistic baseline for comparison with the TEPSI.

Figure 6-8

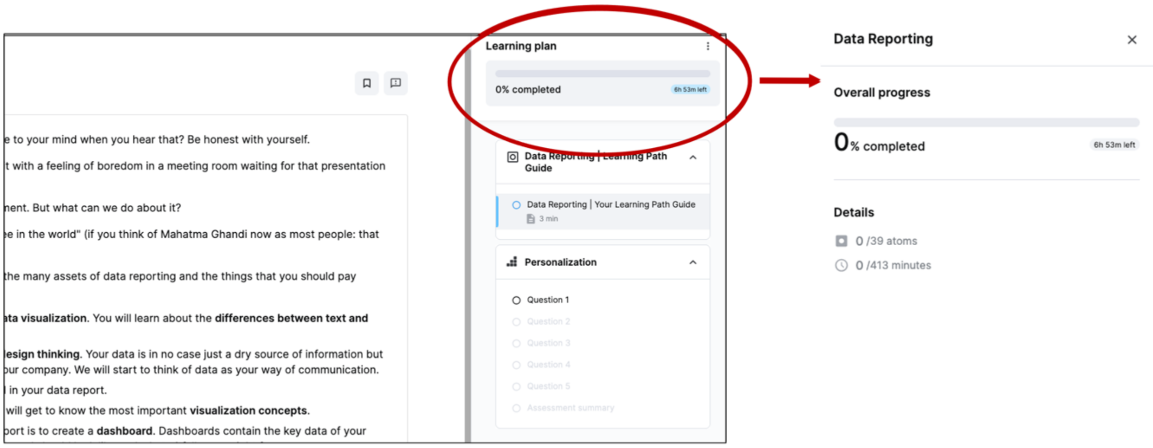
Goal Setting in the Control Condition (Study 1)



Note. By clicking on the widget, learners can specify a weekly goal and track their goal progress on the starting page.

Figure 6-9

Dashboard in the Control Condition (Study 1)



Note. By clicking on the grey widget in the top right corner, learners can open the dashboard.

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.

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 number 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 6-2. Out of the 146 participants, 92 completed the post-questionnaire. Therefore, analyses including information from the post-questionnaire were based on this sub-sample of 92 participants.

Table 6-2

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 M = 38.31 SD = 10.42	Range: 21–56 M = 31.85 SD = 9.14	Range: 24–60 M = 40.19 SD = 11.10	Range: 21–60 M = 37.33 SD = 9.03	Range: 23–62 M = 33.76 SD = 10.68	Range: 21–59 M = 34.91 SD = 10.52	Range: 21–62 M = 36.49 SD = 10.33

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 Figure 6-1). 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 6-1 were assessed using items adapted from the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1991, 1993). 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 $\alpha_{\text{pre-questionnaire}}$ = .80, Cronbach's $\alpha_{\text{post-questionnaire}}$ = .85). Time and study environment was assessed with eight items (e.g., "I make good use of my study time", Cronbach's $\alpha_{\text{pre-questionnaire}}$ = .80, Cronbach's $\alpha_{\text{post-questionnaire}}$ = .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 unsatisfying reliability scores (Cronbach's $\alpha_{\text{pre-questionnaire}}$ = .68, Cronbach's $\alpha_{\text{post-questionnaire}}$ = .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 6-3 were calculated. These variables represent learners' interactions with the core features of the TEPSI, which aim to address the SRL strategies presented in Table 6-1.

Table 6-3

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.

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 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.

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, *t*-tests for independent samples were conducted to analyze whether the experimental conditions differed with regard to 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 6-3. 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.

6.6.2 Results

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 Appendix D.

Research Question 1: Effects of the Availability of the Intervention

The results of the t-tests for learning path completion are presented in Table 6-4. No significant differences between the intervention and the control condition were detected.

Table 6-4

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

Condition	*M*	*SD*	*t*(*df*)	*p*	*d*
All learning paths (*n* = 145)			**−0.46(143)**	**.650**	**−0.08**
Intervention (*n* = 73)	0.65	0.40			
Control (*n* = 72)	0.68	0.38			
Agile Management (*n* = 59)			**−0.54(57)**	**.589**	**−0.14**
Intervention (*n* = 26)	0.65	0.41			
Control (*n* = 33)	0.71	0.36			
Data Reporting (*n* = 37)			**0.04(35)**	**.971**	**0.01**
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**
Intervention (*n* = 27)	0.59	0.39			
Control (*n* = 22)	0.61	0.41			

Note. Of the sample size (N = 146), one participant had to be excluded due to technical problems with the storage of the completed learning materials.

The results of the mixed ANOVAs are presented in Table 6-5 (for means and standard deviations, see Table 6-6). 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: $t(24) = -2.50$, $p = .020$, $d = -0.46$, 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 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 Figure 6-10). No other effects on self-reported time and study environment were significant.

Table 6-5

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

Variable	$F(df1, df2)$	p	$\eta^2_{partial}$
Metacognitive self-regulation			
All learning paths			
Time of measurement	17.84(1, 90)	< .001	.17
Condition	0.02(1, 90)	.895	< .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	< .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	< .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	< .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	< .01
Condition	0.11(1, 28)	.743	< .01
Time of measurement*condition	0.05(1, 28)	.827	< .01

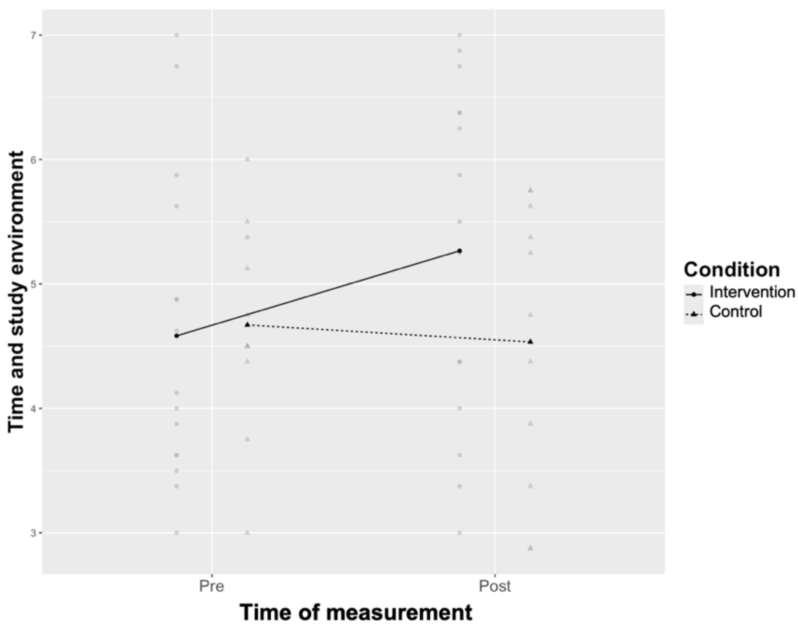
Table 6-6

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	$M = 4.40$, $SD = 1.20$, $n = 17$	$M = 4.35$, $SD = 1.20$, $n = 13$

Figure 6-10

Significant Interaction Effect on Self-Reported Time and Study Environment in the Data Reporting Learning Path (Study 1)



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 6-7, participants in the Data Reporting learning path tended to engage with the TEPSI more actively 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 6-7), potentially due to low statistical power resulting from the small sample sizes.

Table 6-7

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 = .16. Kruskal-Wallis test for sum of dashboard accesses: $H(2)$ = 4.24, p = .120, η^2 = .03. Kruskal-Wallis test for sum of goal modifications: $H(2)$ = 0.76, p = .685, η^2 = .02. Kruskal-Wallis test for percentage of achieved weekly goals: $H(2)$ = 2.01, p = .366, η^2 < .01.

Research Question 2: Effects of Participants' Interactions With the Intervention

As shown in Table 6-8, setting an overall learning goal negatively affected learning path completion and self-reported time and study environment. On the contrary, the percentage of achieved weekly goals was positively related to learning path completion and 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.

Table 6-8

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	< .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	< .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	< .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	< .001

Note. Only participants of the intervention condition were considered.
[a] $F(4, 68) = 25.27$, $p < .001$, $R^2 = .52$, $R^2_{adjusted} = .49$. HC3 correction (Hayes & Cai, 2007) was employed because of heteroscedasticity. [b] $F(5, 40) = 2.76$, $p = .031$, $R^2 = .26$, $R^2_{adjusted} = .16$. [c] $F(5, 40) = 11.19$, $p < .001$, $R^2 = .58$, $R^2_{adjusted} = .53$.

6.6.3 Discussion and Introduction to Study 2

Educational technologies offer potential for providing personalized and timely support for SRL (Nguyen et al., 2024; Wong et al., 2019). 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 (Tan et al., 2017; X. Xu et al., 2024). To design effective TEPSIs for CE, explanations for these ambivalent findings need to be found. 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.

6.7 Study 2

6.7.1 Method

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 (Dillow, 1997; Huang et al., 2025; Konrad, 2020). Such verbalizations may provide detailed information about participants' perceptions and reasoning and have been considered a valuable source for user research (Dillow, 1997; Hertzum, 2024) and for studying individual learning processes (Greene et al., 2011; Huang et al., 2025).

For the present study, we developed an interview guide consisting of an introduction part, a main part, and a reflection part. In the 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 Figure 6-6). 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 Appendix D. The interviewer was free to ask follow-up questions when clarification was needed.

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. A total number 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).

Data Collection

The first six interviews were conducted as part of a master's thesis (Bruynooghe, 2023) 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 minutes (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 6.7.2) were translated into English.

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 (Mayring, 2015). 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 6-1). 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 respective SRL strategy. The coding manual is available in Appendix D.

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.

6.7.2 Results

A summary of the findings is presented in Table 6-9.

Table 6-9

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

Research Question 3: Perceived Ease of Use

Salience. Most participants (n = 15) noticed the TEPSI on the starting page after logging in on the platform. 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 problems 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 difficulties 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 minutes. Previously, it said 55 minutes 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 minutes, but it did not take me 4 minutes" (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 minutes. Previously, I had 3 out of 55 minutes. 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 difficulties spotting the most important information in the dashboard at first glance. For example, when presented with the screenshot "Overdue" (see Figure 6-6), 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 Figure 6-6) 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).

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 more autonomy in organizing their weekly goals (e.g., the option to pause the system if they are on vacation 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.

6.8 General Discussion

SRL strategies have been considered essential for learning success in CE (Hemmler & Ifenthaler, 2024; D. Lee et al., 2019). 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).

6.8.1 Interpretation of Results and Theoretical Implications

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 learning path Data Reporting. These findings are consistent with Z. Xu et al.'s (2023) meta-analysis showing that SRL interventions in K-12 and higher education are more effective 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 (H. Lee & Bosch, 2024). Previous research has highlighted that the learning content can shape SRL and online learning behaviors. For example, learners' use of SRL strategies (Greene et al., 2015; H. Lee & Bosch, 2024) and interaction patterns within online learning environments (Gašević et al., 2016; Song et al., 2024) vary across learning topics and disciplines. Moreover, characteristics of learning activities (e.g., duration, insturctional strategies) can influence individual learning processes, such as SRL strategies (Hemmler & Ifenthaler, 2024) and learning engagement (Heilporn et al., 2022; Rüter & Martin, 2022).

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 (~ 6.5 hours) than Agile Management (~ 5.5 hours) but was shorter than the Leadership in Practice (~ 10 hours) 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 (Y. Lee & Song, 2022), 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 Appendix D). 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 (Heckman, 1990) 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 (Schwarz & Jeworutzki, 2024). 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 (Beheshitha et al., 2016; Duffy & Azevedo, 2015; Lallé et al., 2016).

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. Possibly, other factors (e.g., lack of time, unfulfilled expectations; Eriksson et al., 2017; Wang et al., 2023) might have played a more central role in participants' learning processes than the intervention. For instance, metacognitive strategies and the completion of learning materials require time and effort (Winne, 2011; Zimmerman & Schunk, 2007). 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 helping them monitor and control their insufficient time resources may not be beneficial (Eriksson et al., 2017; Teich et al., 2024).

Study 2 revealed further explanations for the TEPSI's limited effectiveness in supporting learning processes. For example, participants criticized its missing connection to the content of the learning path. SRL involves planning, monitoring, and reflection behaviors that should consider both time and content aspects (Pintrich et al., 1991, 1993; Theobald, 2021). Moreover, participants in Study 2 wished for more support concerning specific features of the intervention (e.g., recommendations to set realistic goals, recommendations for adapting deadlines), which is consistent with previous research showing that learners might need specific instructions on how to make sense of dashboard visualizations (Psathas et al., 2023). Especially learners with limited SRL skills and feedback literacy might need more support to adequately use the information presented by the TEPSI (Bennett & Folley, 2020; Tepgec et al., 2025).

Surprisingly, interacting with the TEPSI of the edyoucated-platform may even negatively affect learning processes. In Study 1, 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. Accordingly, 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 (Tan et al., 2017). 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 (Deci et al., 1996; Ushioda, 2011). 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 problems regarding the ease of use were detected, especially in relation to 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 (Alshammari et al., 2015; An et al., 2024).

Altogether, our findings are consistent with findings from previous studies showing limited effectiveness of TEPSIs in supporting learning processes in CE (e.g., Psathas et al., 2023; Teich et al., 2024). Despite the potential of TEPSIs discussed in previous literature (Nguyen et al., 2024; Prasse et al., 2024), 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, researchers have objected that the continuous support provided by TEPSIs might hinder SRL by making learners dependent rather than encouraging self-regulation (Howell et al., 2018; Schumacher, 2019). 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, negative side effects may be prevented (Alshammari et al., 2015; Park et al., 2023).

6.8.2 Practical Implications

Our studies have several implications for designing 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 (H. Lee & Bosch, 2024).

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 (Eriksson et al., 2017; Wang et al., 2023), 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 (Fromm & Ifenthaler, 2024).

Third, TEPSIs for CE should provide holistic support for SRL, considering aspects related to both time and learning content (Theobald, 2021; Z. Xu et al., 2023). For example, dashboards should visualize learning progress based on learning content rather than only time-related aspects (Park et al., 2023). Further, TEPSIs could provide personalized scaffolds that help learners apply appropriate strategies to engage with the learning materials (Li et al., 2023).

Fourth, since learners in CE may have difficulties setting realistic learning goals (Nguyen et al., 2024) and making sense of dashboard visualizations (Psathas et al., 2023), 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 (Tan et al., 2017).

Fifth, since learners in CE are distinguished by a strong need for self-direction (Knowles et al., 2012; Manning, 2007), TEPSIs for CE should not be overly prescriptive and give learners autonomy in planning and organizing their learning processes (Teich et al., 2024). 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 (Howell et al., 2018; Schumacher, 2019).

Sixth, continuous adaptation and personalization of learning activities can create complexity and reduce learners' perceived ease of use (Alshammari et al., 2015; An et al., 2024). Therefore, TEPSIs should provide specific explanations regarding the SRL support (Graf, 2023; Idrizi, 2024). For example, mouseover effects could clarify dashboard visualizations (Rodda, 2023).

6.8.3 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, and the sample size was rather small, particularly when considering the three learning paths separately. Therefore, future research examining TEPSIs for CE should use a larger sample 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, since Study 1 took place entirely online, we have no control over how deeply participants engaged with the learning materials. Thus, the measurement of learning path completion might be biased. Moreover, the self-reported SRL strategies might be subject to subjective biases, such as social desirability (Lavidas et al., 2022; Van de Mortel, 2008) or individual response styles (Tempelaar et al., 2020). Therefore, future research should evaluate TEPSIs for CE in more controlled settings and employ behavioral measures of SRL strategies (Du et al., 2023) to examine differences between intervention and control conditions.

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 while interacting with the TEPSI, we opted for the think-aloud method instead of conducting retrospective interviews with participants from Study 1. Nevertheless, future research should qualitatively investigate learners' perceptions of TEPSIs after using such interventions during their learning process.

6.8.4 Conclusion

CE has been considered important for keeping knowledge, skills, and competences up-to-date (Mlambo et al., 2021; Omar et al., 2024) and requires learners to engage in SRL (D. Lee et al., 2019; Zimmerman & Schunk, 2011). Researchers have emphasized the potential of educational technologies to provide personalized support for SRL (Nguyen et al., 2024; Prasse et al., 2024). However, 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.

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7. Discussion

7.1 Summary of Findings

The multi-method approach adopted by the four research papers of this thesis provides user-centered and empirical findings on adaptive learning environments (ALEs) and self-regulated learning (SRL) in continuing education (CE). These findings answer the overarching research question of this thesis (*How can the design of ALEs for CE be optimized to support SRL and positive learning outcomes?*) by addressing the different research foci introduced in Section 1.2.

7.1.1 Stakeholders' Perspectives on Indicators and Interventions

Effective ALEs require reliable and meaningful indicators and interventions for personalizing and supporting learning processes (Aleven et al., 2017; K. C. Li & Wong, 2023; Plass & Pawar, 2020b; Yau & Ifenthaler, 2020). To develop a user-centered and empirically-based framework for selecting indicators and interventions for ALEs in CE, Paper 1 investigated the perceptions and expectations of three relevant stakeholders: learners, CE specialists, and educational technology specialists. In this regard, Paper 1 contributes to the design of ALEs by identifying indicators that are relevant to learning processes and outcomes in CE, highlighting interventions that meet learners' specific needs, and illustrating which interventions may be feasible to implement in CE. These insights may help design trustworthy ALEs that are accepted by learners (Gril et al., 2022; Topali et al., 2025) and overcome implementation challenges in CE practice (Fake & Dabbagh, 2020).

Three key findings for the design of ALEs may be summarized from Paper 1. First, since learners may enter a CE activity with diverse prior experiences and varying levels of prior knowledge (Knowles et al., 2012; Meister & Willyerd, 2021; Wozniak, 2020), the findings highlight the need for personalized learning interventions that consider these differences. For instance, learners in Paper 1 prioritized an intervention that adjusts the general difficulty level or thematic focus of the CE activity to their individual prior experiences or knowledge. Second, the findings of Paper 1 emphasize the need for ALEs that support SRL and learners' efficient usage of their time resources. Several indicators (e.g., resource management strategies, time available for learning) and interventions (e.g., individual reminders, recommendation of learning resources based on available time) related to learners' SRL strategies and personal time resources were identified as relevant to CE. These findings are consistent with previous research indicating that ineffective SRL strategies and lack of time are major barriers to CE

(Eriksson et al., 2017; Nawrot & Doucet, 2014; W. Wang et al., 2023). Third, the findings of Paper 1 highlight that CE activities should be tailored to the interests and everyday tasks of learners. For instance, several interventions (e.g., context adaptation, recommendation of learning resources based on interests or the working area) that tailor learning activities to learners' personal interests or highlight learners' personal benefits of the CE activity for their everyday (work) lives were identified.

The findings of Paper 1 served as the basis for the subsequent papers, in which the identified indicators and interventions were further elaborated and examined. Building on the first key finding mentioned above, a personalized learning intervention tailoring learning activities to individual learners' prior knowledge was evaluated in Paper 2. Moreover, according to the second key finding, the nature of SRL in CE has been further explored in Paper 3, and an intervention to support SRL in CE was implemented and evaluated in Paper 4.

7.1.2 Effectiveness of Adaptive Learning Environments

The effectiveness of ALEs in supporting learning processes in CE was evaluated by the two experimental studies presented in Paper 2 and Paper 4. Paper 2 investigated the effects of a technology-enhanced personalized learning environment based on prior knowledge (TEPLE-PK) that allows learners to skip learning content based on their individual level of prior knowledge. The findings revealed nuanced effects on knowledge increase and learner satisfaction in CE, which were moderated by learners' goal orientations and task value. The findings of Paper 2 highlight that while TEPLEs-PK may effectively support learning processes in CE, not every learner benefits equally from the same type of personalized learning support. Moreover, the findings of Paper 2 indicate that learners in CE tend to answer honestly and reflectively when prompted to self-report their prior knowledge. Contrary to previous research criticizing self-report questionnaires for being subject to subjective biases (Lavidas et al., 2022; Snibsøer et al., 2018; Tempelaar et al., 2020; Van de Mortel, 2008), Paper 2 suggests that self-report questions may be a useful tool for measuring prior knowledge in TEPLEs-PK for CE.

Contrary to our expectations, the TEPLE-PK investigated in Paper 2 did not affect learning path completion, and the dropout rate from the CE activity was high (~ 85%). Assuming that supporting SRL strategies would enhance learning persistence (Nawrot & Doucet, 2014; Sitzmann & Ely, 2011), a technology-enhanced personalized SRL intervention (TEPSI) was implemented and evaluated in Paper 4. The TEPSI consisted of a goal-setting functionality, a personalized learning plan, and a personalized dashboard that were integrated into the TEPLE-PK from Paper 2. However, the findings of Paper 4 revealed the limited effectiveness of the TEPSI in supporting SRL in CE. The TEPSI had a positive effect on learners' perceived time and study environment, but only in one out of three learning paths. These findings again highlight the context-dependent effects of ALEs, showing that different learners in different learning contexts may benefit differently from the same type of personalized learning support. The nuanced effects of Paper 2 and Paper 4 align with previous research on higher education suggesting that the effects of personalized learning support depend on learners' internal conditions, such as goal orientations (Duffy & Azevedo, 2015; Lallé et al., 2016) and learning strategies (T. Li et al., 2025), as well as external conditions, such as the learning content (H. Lee & Bosch, 2024) and instructional characteristics (Gašević et al., 2016). Further, analyses in Paper 4 revealed that interacting with the TEPSI could even negatively affect learning processes if learners could not adhere to the provided learning time recommendations. Overall, the findings of Paper 4 align with previous studies that demonstrate the limited effectiveness of TEPSIs in supporting learning processes (Heikkinen et al., 2023; Psathas et al., 2023; Teich et al., 2024). Paper 4 concludes that personalization is no miracle cure and that TEPSIs alone are insufficient to address deeper-rooted problems, such as lack of time or unfulfilled expectations, which impair learning experiences in CE (Eriksson et al., 2017; W. Wang et al., 2023).

7.1.3 Nature of Self-Regulated Learning in Continuing Education

To effectively support SRL in CE, insights into how SRL unfolds in CE are needed (Cuyvers et al., 2020; Panadero, 2017). Therefore, Paper 3 employed a systematic review and meta-analysis to explore potential antecedents and outcomes of learners' use of SRL strategies in CE. The findings highlight learning process-related (e.g., achievement motivation), learner-related (e.g., prior knowledge), CE-related (e.g., peer interaction), and work-related (e.g., organizational learning culture) factors associated with learners' use of SRL strategies in CE and show that the strength of the underlying relationships may depend on the operationalization of variables (subjective vs. objective), the setting (online vs. face-to-face), and the work-relatedness (work-related vs. non-work-related) of the CE activity. Moreover, compared to other meta-analyses focusing on K-12 education (e.g., J. Li et al., 2018) and higher education (e.g., Broadbent & Poon, 2015), the findings show stronger average correlations between SRL strategies and learning performance, especially for metacognitive and resource management strategies. Further, the findings once again highlight that learners' limited time resources constitute a key barrier to CE, as lack of time may hinder successful SRL. Consequently, the TEPSI designed for Paper 4 aimed to support learners' metacognitive and resource management strategies in CE while specifically focusing on learners' personal time resources.

However, as mentioned in Section 7.1.2, this TEPSI was only partially effective in supporting SRL in CE.

7.1.4 Perceived Ease of Use and Usefulness

To further explore the limited effectiveness of the TEPSI introduced in Paper 4, an additional interview study was conducted. Using the think-aloud method, this interview study explored learners' perceived ease of use and usefulness of the TEPSI. The findings highlight several weaknesses and opportunities for optimization that may inform the design of TEPSIs and ALEs for CE. For example, the findings underscore the necessity of holistic support for SRL that considers not only time but also learning content-related aspects of SRL. Further, the findings show that continuous negative feedback, perceived restrictions of learner autonomy, and the complexity resulting from continuous adaptation and personalization may impair rather than support learning processes. By linking these findings with previous research, Paper 4 concludes that the development of less prescriptive interventions (Teich et al., 2024; Wozniak, 2020) and the provision of detailed explanations and instructions for use (Graf, 2023; Idrizi, 2024; Psathas et al., 2023) could mitigate these negative effects.

7.2 Theoretical Implications

A synthesis of the findings from all four research papers indicates the potential of this thesis to advance theories on ALEs, SRL, and CE. In particular, the findings of this thesis provide two major theoretical implications, which are discussed in the following two sections.

7.2.1 Adaptive Learning Environments and Adult Learning Theory

The findings of this thesis can be interpreted using adult learning theory (Knowles, 1980; Knowles et al., 2012). Accordingly, this thesis provides empirical evidence for adult learning theory and highlights how the principles of adult learning theory may offer a theoretical basis to guide the design of ALEs for CE. Adult learning theory explains how the learning experiences of adult learners in CE differ from those of younger learners in K-12 and higher education. The theory consists of six assumptions about adult learning that relate to the learners' (1) independent self-concept, (2) prior experiences, (3) source of motivation, (4) orientation to learning, (5) readiness to learn, and (6) need to know (Knowles, 1980, 1985; Knowles et al., 2012).

The first assumption of adult learning theory (independent self-concept) claims that adult learners are characterized by a strong need for self-direction (Knowles et al., 2012; Manning, 2007). As a normal aspect of maturation, individuals' self-concept shifts from that of a dependent personality to that of an independent and self-directed personality as they become older (Kawalilak & Groen, 2021; Knowles, 1980). Therefore, adult learners want to be responsible for their learning and resist when others try to force their will upon them (Knowles, 1985; Knowles et al., 2012). Accordingly, this thesis highlights that prescriptive ALEs may negatively impact learning motivation, emphasizing the importance of learner autonomy and control. For instance, in the interview study of Paper 4, the implemented TEPSI was criticized for its prescriptive time allocations, which may not have aligned with the learners' independent self-concept. In Paper 2, learner autonomy and control were addressed by allowing learners to correct the prior knowledge assessments of the TEPLE-PK and by not removing the learning content that could be skipped due to personalization. As such, learners could supervise the personalization system and intervene if they had concerns about its reliability. Moreover, to satisfy learners' need for self-direction, Wozniak (2020) argued that ALEs should prompt learners about specific indicators (e.g., prior knowledge, interests) directly instead of inferring these indicators solely from indirect measures, such as learners' usage of the system. Although self-reports may introduce bias (Lavidas et al., 2022; Snibsøer et al., 2018; Tempelaar et al., 2020; Van de Mortel, 2008), Wozniak (2020) argued that adult learners in CE might have a stronger ability to self-reflect and self-analyze than younger students. This is consistent with the findings of Paper 2, suggesting that learners in CE tend to report honestly and reflectively on their prior knowledge.

According to the second assumption of adult learning theory (prior experiences), adult learners are characterized by the unique experiences they have accumulated in the course of their lives. These experiences represent a rich resource for learning on which adult learners want to build (Knowles, 1980; Knowles et al., 2012). Therefore, Wozniak (2020) argued that ALEs for CE should consider learners' prior experiences, tailoring learning activities to what the individual learner already knows or can do. Accordingly, the findings of Paper 1 emphasize personalized learning interventions that consider learners' prior experiences and knowledge. Moreover, although the effects depended on learners' motivational dispositions, the findings of Paper 2 suggest that personalization based on prior knowledge can positively affect learning outcomes in CE.

The third assumption of adult learning theory (source of motivation) claims that the most potent motivators in adult learning are internal (e.g., desire to increase job satisfaction or self-esteem; Knowles et al., 2012). Therefore, Wozniak (2020) assumed that ALEs could enhance learning experiences by tailoring learning activities to individual learners' interests and preferences. Paper 1 identified interventions that align with this assumption, such as the recommendation of learning resources based on interests. However, in (corporate) work-related CE, the source of learning motivation may be external and regulated by the employer rather than internal (de Jong et al., 2025; Hemmler et al., 2023). Accordingly, the findings of Paper 3 suggest that the connection between achievement motivation and SRL may differ between work-related and non-work-related CE. (Corporate) work-related CE should satisfy not only the interests of the learner but also the interests of the work organization, and ALEs need to incorporate both the learner's and the organization's perspectives (Hemmler et al., 2023).

The remaining three assumptions of adult learning theory suggest that adult learning is life-centered rather than subject-centered (orientation to learning), that adult learners are ready to learn what they need to learn to cope efficiently with problems in their real lives (readiness to learn), and that adult learners need to know why they have to complete a specific learning task and how this learning task benefits them in their daily lives (need to know; Knowles, 1980; Knowles et al., 2012). These assumptions are consistent with several interventions identified in Paper 1 that highlight learners' personal benefits of the learning activity. For example, interventions such as context adaptation (i.e., adaptation of the context of the learning content to the learner's job tasks) and emphasis of personal relevance (i.e., pop-ups or short hints that highlight the personal relevance of the learning content to the learner's everyday life) aim to demonstrate the value of the CE activity for the learner's everyday (work) life.

7.2.2 (Supporting) Self-Regulated Learning in Continuing Education

This thesis contributes to SRL theories by highlighting how SRL unfolds in CE. Paper 3 illustrates patterns in SRL strategies that provide useful insights to advance existing SRL theories and adapt them to the context of CE. For example, Paper 3 provides a model identifying factors associated with learners' use of SRL strategies in CE that may help explain SRL processes. Hence, while several SRL theories focusing on K-12 and higher education have postulated that SRL is shaped by personal and contextual characteristics (Järvelä & Hadwin, 2013; Pintrich, 2000; Winne, 2022; Winne & Hadwin, 1998; Zimmerman, 2000), Paper 3 contributes to these theories by highlighting the specific factors (e.g., lack of time available for learning, organizational learning culture) that shape SRL in CE.

Furthermore, the findings of Paper 4 underscore the limited effectiveness of TEPSIs in CE. Although this lack of effectiveness may be attributable to some extent to issues related to the design of the implemented TEPSI, considering the findings of Paper 4 alongside those of Paper 3 implies that TEPSIs may only treat symptoms of SRL problems in CE rather than the root cause. Although effective SRL strategies have been considered essential for CE (Cuyvers et al., 2020; D. Lee et al., 2019), interventions only addressing SRL strategies may not be sufficient to enhance learning persistence. It is also necessary to create conditions that enable learners to actually apply SRL strategies in their everyday learning, such as by providing them with sufficient time resources or fostering an organizational learning culture (Hosseini et al., 2020; Kittel et al., 2021; Milligan & Littlejohn, 2016; Vanslambrouck et al., 2019).

7.3 Practical Implications

The user-centered and empirical insights generated by this thesis provide several implications for designing ALEs for CE. Building on the study-specific practical implications discussed in Chapters 3–6, the following main practical implications can be derived from the findings of this thesis.

7.3.1 Considering the Context-Dependent Effects of Adaptive Learning Environments

Since this thesis highlights the context-dependent effects of ALEs, it is crucial to thoroughly examine the contexts in which specific interventions are beneficial before implementing them for CE. Moreover, the diverse needs of learners in CE may require ALEs that are responsive to multiple indicators. Since different learners may benefit from different types of learning support, personalized learning interventions based on only one indicator (e.g., prior knowledge) may not be sufficiently personalized. However, the integration of multiple indicators into an ALE may increase the complexity of the learning system, which may create new challenges (Plass & Pawar, 2020b). For example, the collection and analysis of multiple indicators may reduce learners' perceived ease of use (Alshammari et al., 2015; An et al., 2024) or create a feeling of constant surveillance (Tsai, Perrotta, & Gašević, 2020). Therefore, the selection and integration of indicators should be guided by learning theories and robust empirical findings (Giannakos & Cukurova, 2023; Plass & Pawar, 2020b; Tsai, Perrotta, & Gašević, 2020). The development of effective ALEs requires a profound understanding of how different indicators interact with each other and which interventions are most appropriate based on specific indicators of learners' internal and external conditions (Beheshitha et al., 2016; T. Li et al., 2025). In this regard, the empirical list of indicators identified in Paper 1 may serve as a useful starting point for developing ALEs that are responsive to multiple indicators. Selecting the most relevant indicators from this list for a specific learning context and analyzing how these indicators interact with each other can help design meaningful interventions.

7.3.2 Ensuring Learner Autonomy and Control Through Transparent and Explainable Adaptive Learning Environments

The findings of this thesis emphasize that ALEs for CE should be non-prescriptive rather than prescriptive, ensuring learner autonomy and control. To satisfy learners' need for self-direction (Knowles et al., 2012; Manning, 2007), ALEs for CE should provide learners with various individualized options to select from (Plass & Pawar, 2020a; Wozniak, 2020) and enable them to make data-informed decisions about their learning (Gharahighehi et al., 2024; Tsai, Perrotta, & Gašević, 2020) rather than prescribing specific learning content or a learning schedule. Moreover, caution is advised when personalization restricts learners' access to certain learning resources, as this might create a feeling of unfair treatment and potentially lead to inequitable learning outcomes (Tsai, Perrotta, & Gašević, 2020). Thus, to promote learner autonomy and control, ALEs may highlight learning resources that are particularly suitable for the individual learner while ensuring access to additional resources. This approach was exemplified by the personalization system in Paper 2, where learning content that could be skipped due to personalization was not removed from the learning path.

Another important principle to ensure learner autonomy and control is transparency (Gharahighehi et al., 2024; Tsai, Perrotta, & Gašević, 2020). To be responsible for their learning and to control their learning processes, learners need to know what information is collected by ALEs, how and for what purposes this information is analyzed, as well as what decisions are made based on the analyses (Ifenthaler & Schumacher, 2019; Simbeck, 2024). In this regard, open learner models have been considered a valuable tool to enhance transparency (Gharahighehi et al., 2024; Kay et al., 2022). Open learner models aim to feed the information collected by ALEs back to the individual learner, enabling them to reflect on and craft their learning, as well as to correct the information if necessary (Hooshyar et al., 2020; Khosravi et al., 2022). Paper 2 demonstrates an example of an open learner model. By providing learners with a summary of the prior knowledge assessment and enabling them to correct the assessment, the presented personalization system ensures transparency, as well as learner autonomy and control.

The findings of this thesis further highlight the need for explainable ALEs. For example, the intervention implemented in Paper 4 was criticized for not being explainable, as learners had difficulties understanding the calculation of the weekly learning time recommendations. Explainability in the context of ALEs refers to the degree to which human users can interpret and understand the decisions made by the learning system (Idrizi, 2024; Simbeck, 2024). The aim of explainable ALEs is to enhance users' trust in and acceptance of the learning system (Dawodu et al., 2025; Feldman-Maggor et al., 2025). Moreover, explainability may enhance transparency, thereby promoting learner autonomy and control (Gharahighehi et al., 2024; Simbeck, 2024). Researchers have introduced several methods for developing explainable ALEs, such as visualizations illustrating the reasons for specific decisions made by the learning system and measures of variable importance in complex artificial intelligence (AI) models (Brdnik et al., 2023; Khosravi et al., 2022). Moreover, learning theories and empirical findings may advance the development of explainable ALEs, as they can explain fundamental mechanisms of learning and may help identify meaningful indicators and interventions (Giannakos & Cukurova, 2023; Omar et al., 2024; Plass & Pawar, 2020b). In this regard, this thesis contributes to the design of explainable ALEs by providing empirical insights into (self-regulated) learning processes and the effectiveness of specific interventions in CE.

7.3.3 Adapting to Learners' Prior Experiences, Interests, and Personal Benefits

According to adult learning theory (Knowles, 1980; Knowles et al., 2012), ALEs for CE should tailor learning activities to individual learners' prior experiences and interests, as well as highlight learners' personal benefits of the learning activities (Wozniak, 2020). To this end, Paper 1 provides several example interventions (e.g., recommendation of learning resources based on interests, emphasis of personal relevance). By integrating these interventions into a design framework that provides insights into learners' willingness to use the interventions, their perceived learning support, and the technological and organizational implementation effort, the findings of Paper 1 provide practical guidance for implementing such interventions in CE. Moreover, Paper 2 of this thesis provides an example of an ALE that is responsive to learners' prior knowledge. The TEPLE-PK evaluated in Paper 2 may serve as a prototype for future learning systems in CE. By highlighting the potentials of this TEPLE-PK in supporting learning processes in CE and demonstrating the conditions under which such learning systems are beneficial, the findings of Paper 2 provide guidance for effective implementation.

7.3.4 Recognizing the Limits of Personalization

This thesis further provides practical implications for supporting learning processes in CE by highlighting that personalization is no miracle cure. While ALEs have received significant attention in recent literature (K. C. Li & Wong, 2023; Merino-Campos, 2025), the limits of personalization need to be recognized and acknowledged. Personalization alone cannot resolve problems whose causes are external to the learning systems. For instance, barriers to SRL and learning persistence in CE, such as lack of time and motivation (Eriksson et al., 2017; W. Wang et al., 2023), must be addressed at their root cause. Although the TEPLE-PK presented in Paper 2 can help learners save time by skipping learning content based on learners' prior knowledge, this time-saving feature only addresses the symptoms and not the underlying cause of time issues in CE. Moreover, as proposed by Paper 4, TEPSIs cannot support SRL strategies in CE if learners lack the time to apply such strategies. As suggested in Paper 3, work organizations may play an important role in supporting learners' use of SRL strategies in work-related CE. For example, allowing employees to allocate work hours for CE may help resolve time issues (Eriksson et al., 2017; Vanslambrouck et al., 2019). Further, employers should emphasize an organizational learning culture and an inspiring work environment that supports employees' engagement in CE activities (Gijbels et al., 2012; Kittel et al., 2021; Raemdonck et al., 2014). In non-work-related CE, time and motivation issues result from learners' individual priorities (Eriksson et al., 2017). If individuals decide to prioritize other tasks, such as family and professional commitments, over voluntarily participating in a CE activity, ALEs may help find suitable CE activities that align with learners' individual time and motivational resources. However, if learners refrain from a specific CE activity due to other commitments, personalized interventions visualizing their poor learning progress may cause pressure and hinder rather than support learning processes (Tan et al., 2017).

7.4 Limitations and Future Research

This thesis shows several limitations that may guide future research. Beyond the study-specific limitations discussed in Chapters 3–6, the following sections outline the general limitations of this thesis and their main implications for future research.

7.4.1 Gaining Profound Insights Into the Context-Dependent Effects of Adaptive Learning Environments

While the findings of this thesis provide first insights into the context-dependent effects of ALEs in CE, additional research is needed to gain a profound understanding of the nuanced effects of different interventions and to establish valid guidance for developing ALEs that are responsive to multiple indicators. For example, only two sets of moderators (goal orientations and task value) were investigated in Paper 2. Previous research indicates that further indicators of learners' internal and external conditions may moderate the effects of ALEs on learning processes and outcomes. For instance, in recent meta-analyses focusing on K-12 and higher education, several moderators of the effects of ALEs on learning outcomes were identified, such as learners' educational level (Tlili et al., 2024; X. Wang et al., 2024), the subject domain (Lin et al., 2024; Tlili et al., 2024; X. Wang et al., 2024), and the application scenario (Hu, 2024). Therefore, future research should investigate additional moderators that could influence the effectiveness of ALEs in supporting learning processes in CE. Moreover, while motivational dispositions (goal orientations and task value) were identified as significant moderators in Paper 2, it remains unclear whether developing ALEs that are responsive to both learners' prior knowledge and motivational dispositions may enhance learning outcomes. Therefore, future research should compare the effectiveness of ALEs that consider different indicators. In addition, further research is needed to elucidate the reasons why the TEPSI examined in Paper 4 affected learners' perceived time and study environment in only one of the three learning paths.

Furthermore, while the findings of this thesis suggest that ALEs for CE should ensure learner autonomy and control, the degree to which learner autonomy and control should be emphasized over guidance by the learning system may also be context-dependent and influenced by learners' internal and external conditions. For instance, while some learners may have a high need for autonomy, others may feel overwhelmed when granted too much control (Gharahighehi et al., 2024). ALEs may be arranged along a dimension ranging from full learner control to fully automated or prescriptive interventions (Gharahighehi et al., 2024; Molenaar, 2022), and the optimal balance between these two extremes for individual learners in CE still needs to be determined. Similarly, researchers have suggested that there is no one-size-fits-all solution to explainable ALEs, as learners may differ in their individual needs for explainability (Gharahighehi et al., 2024; Kim, Maathuis, & Sent, 2024; Liao & Varshney, 2021). For instance, studies have shown that the effectiveness of explanation techniques for AI models may depend on contextual factors, such as individuals' AI experience (Ghai et al., 2021), personality traits (Conati et al., 2021; Ghai et al., 2021), and the specific application scenario (Kim, Maathuis, van Montfort, & Sent, 2024). Therefore, future research should evaluate the effectiveness of different explanation techniques for ALEs for CE and their dependency on learners' individual conditions. Hence, future research may address the following research questions to gain profound insights into the context-dependent effects of ALEs:

- What indicators of learners' internal and external conditions moderate the effects of ALEs on learning processes and outcomes in CE?
- Are ALEs that are responsive to multiple indicators (e.g., prior knowledge and motivational dispositions) more effective in supporting learning processes and outcomes in CE than ALEs that consider only one type of indicator?

- How can the optimal balance between learner control and guidance by ALEs be identified to provide the best possible learning support in CE?
- Depending on their internal and external conditions, how do learners in CE evaluate the usefulness of different explanation techniques (e.g., visualizations, measures of variable importance) for explainable ALEs?

7.4.2 Investigating the Long-Term Effects of Adaptive Learning Environments

Although the two experimental studies conducted in Paper 2 and Paper 4 offer empirical insights into the effectiveness of ALEs in supporting learning processes in CE, additional research is needed to investigate the long-term effects of ALEs in CE. In the two experimental studies of this thesis, learning performance was measured as knowledge increase and learning path completion. However, this thesis did not consider the transfer of the acquired knowledge into everyday (work) life. Thus, the capacity of ALEs to affect behavioral changes and distal results (e.g., productivity, turnover) remains unclear. Such outcomes have been considered important criteria for the success of CE activities, as CE typically serves not only to acquire knowledge but also to develop skills and competences that benefit learners in their everyday (work) lives (Hajdari et al., 2023; Kirkpatrick, 2007; Magwenya et al., 2023). Moreover, ALEs may support knowledge transfer by providing specific interventions that foster the long-term effects of CE activities. For example, ALEs could send adaptive reminders that prompt learners to apply the acquired knowledge to real problems or model individual forgetting curves for spaced repetition (Zaidi et al., 2020). Therefore, future research should conduct experimental studies that not only focus on pre-post comparisons but also include follow-up measurements to investigate the long-term effects of ALEs. This approach could address the following research questions:

- How do the effects of ALEs on learning processes and outcomes in CE change over time?
- Can ALEs enhance behavioral and distal outcomes of CE activities?
- How can ALEs foster learners' knowledge transfer after CE activities?

7.4.3 Exploring the Role of Human Instructors and the Potential of Design-Loop Interventions

This thesis focused on the evaluation of ALEs for supporting individual learning processes in CE while neglecting to address the role of human instructors. ALEs have been considered a valuable tool in circumstances where the number of learners exceeds a human instructor's capacity to provide personalized instruction (D. Lee et al., 2018; Rachmad, 2022).

Therefore, a comparative experimental analysis between personalized instruction provided by ALEs and that of human instructors is imperative to gain a profound understanding of the benefits and weaknesses of ALEs. In addition, researchers have argued that ALEs should augment rather than replace human instruction (Molenaar, 2022; Tsai, Perrotta, & Gašević, 2020). ALEs ought to function as co-facilitators collaborating with human instructors to design learner-centered and dynamic CE activities (Qureshi, 2025). For example, ALEs may assist human instructors' decision-making by analyzing education-related data, providing actionable insights, and giving data-informed recommendations (Curran et al., 2024; Molenaar, 2022). Concurrently, human instructors can contribute their expertise in education and human factors such as emotional intelligence and ethical reasoning (Qureshi, 2025). Therefore, future research should investigate how ALEs and human instructors can inform each other to design meaningful learning experiences in CE. This research should include user-centered design approaches that provide insights into instructors' hopes and concerns regarding ALEs for CE and actively involve instructors in the development of ALEs rather than confronting them with the end product (Gharahighehi et al., 2024; Topali et al., 2025). Moreover, instructors must be equipped with the necessary skills, such as data literacy skills, to evaluate the analyses and recommendations of ALEs critically. Therefore, future research should develop appropriate CE programs for instructors (Barrera Castro et al., 2025; Ifenthaler, 2022; Qureshi, 2025).

Furthermore, future research should put more emphasis on design-loop interventions for CE. While the studies of this thesis mainly focused on personalized learning interventions, ALEs may also enhance learning experiences by adapting to similarities between learners. For instance, ALEs may provide actionable insights and recommendations to improve curricula by identifying common challenges faced by learners (Aleven et al., 2017). In particular, since this thesis highlights the limits of personalization, the potential of ALEs beyond personalized learning should be further explored. In Paper 1, only one design-loop intervention was identified. Therefore, future research needs to apply more focused approaches that investigate instructors' and educational decision-makers' perceptions of design-loop interventions. Altogether, future research may address the following research questions to explore the role of human instructors in ALEs for CE and the potential of design-loop interventions:

- How effective are personalized learning interventions provided by ALEs in supporting learning processes in CE compared to human instruction?
- What are the hopes and concerns of human instructors regarding ALEs for CE?
- How can ALEs and human instructors collaborate to improve learning processes and outcomes in CE?

- How can human instructors be trained to effectively incorporate ALEs into CE activities?
- According to human instructors and educational decision-makers, what design-loop interventions are useful and feasible for CE?

7.4.4 Investigating Different Types of Continuing Education

CE encompasses a wide variety of learning activities, such as online and face-to-face, work-related and non-work-related, as well as formal, non-formal, and informal learning activities, which differ in the way learning takes place (Schiersmann, 2007; Tynjälä, 2008, 2013; Widany, 2021). Accordingly, Paper 3 highlights that SRL patterns may differ between work-related and non-work-related CE. However, the present thesis neglected to explore the effects of ALEs on learning processes and outcomes in different types of CE. Paper 1 aimed to identify and evaluate indicators and interventions for ALEs, drawing on participants' previous experiences with online CE. Although no restrictions regarding work-relatedness and formality were made in Paper 1, unconscious informal learning processes might have been disregarded, as the findings relied on learners' conscious experiences. Paper 2 and Paper 4 focused on non-formal CE activities offered online. Participants might have engaged in these CE activities for both work-related and non-work-related reasons, but participation was voluntary and not regulated by the participants' employers. Thus, especially face-to-face, corporate work-related, as well as formal and informal learning activities were neglected in this thesis.

Although ALEs have been typically realized in online learning settings (Alonso et al., 2025; Plass & Pawar, 2020a), face-to-face learning settings are also increasingly supported by educational technologies, such as learning platforms or learning apps (Bundesministerium für Bildung und Forschung [BMBF], 2024; Widany, 2021). Therefore, ALEs can be implemented not only in purely online settings, and future research should investigate how ALEs can support learning processes in face-to-face and blended CE activities. For example, ALEs may support learners in self-study phases while concurrently providing instructors with information regarding learners' progress (Contrino et al., 2024). Moreover, additional research is needed to explore the potential of ALEs in work-related compared to non-work-related CE, as well as in corporate work-related compared to individual work-related CE. For example, ALEs might need to adapt their behavior depending on whether the CE activity is regulated by the employer or the individual learner. In corporate CE activities regulated by the employer, ALEs may restrict learners from exploring different learning resources, enabling them to focus on the learning goals set by the employer. In contrast, if the CE activity is not regulated by the employer but by the learners themselves, ALEs should allow learners to explore different learning resources based on their individual interests (Hemmler et al., 2023). Furthermore, future research should investigate how ALEs may capture and support informal learning processes in CE. For instance, digital technologies used at work (e.g., internal wikis, networking services) may be used to track informal learning processes and provide personalized recommendations of information resources or colleagues with whom to exchange ideas (Schumacher, 2018). Thus, future research should explore the potential of ALEs in supporting learning processes in different types of CE by addressing the following research questions:

- What kind of support can ALEs provide to facilitate learning processes in face-to-face and blended CE activities?
- How should the support provided by ALEs be adjusted depending on the work-relatedness and the regulation (learner vs. employer) of the CE activity?
- How can ALEs capture and support informal learning processes in CE?

7.4.5 Exploring Alternative Perspectives and Theories on the Regulation of Learning

Although Paper 3 provides useful insights into the factors associated with learners' use of SRL strategies in CE, its innovative power for the context of CE is subject to some limitations. For example, several of the primary studies (e.g., Martinez-Lopez et al., 2017; Schulz & Roßnagel, 2010) included in the systematic review and meta-analysis were based on SRL theories focusing on K-12 and higher education (e.g., Pintrich, 2000; Zimmerman, 2000). Moreover, the reviewed SRL strategies were analyzed and coded based on Pintrich et al.'s (1991, 1993) classification of cognitive, metacognitive, and resource management strategies, which was originally developed for higher education. Although researchers have argued that the reviewed SRL strategies may be applicable to the context of CE (Fontana et al., 2015; Kittel et al., 2021), future research should re-evaluate these SRL strategies for different types of CE. For instance, SRL has been defined as a goal-directed process in which the reviewed SRL strategies aim to help learners achieve their personal learning goals or meet defined standards (Pintrich, 2000; Puustinen & Pulkkinen, 2001; Winne, 2011; Winne & Hadwin, 1998). However, informal CE may occur spontaneously and unconsciously without explicit learning goals or standards (Cuyvers et al., 2020; Eraut, 2004; Schumacher, 2018), and it remains unclear whether the reviewed SRL strategies accurately describe the regulation of learning in such contexts. Moreover, this thesis adopted a primarily individualistic perspective on SRL. However, since society and workplaces often require individuals to collaborate in teams, future research should put more emphasis on the co-regulation and socially shared regulation of learning in CE (Hadwin et al., 2011; Järvelä & Hadwin, 2013) and on how they can be supported by ALEs (Sharma et al., 2024).

In addition, future research should identify indicators of effective SRL in CE. For example, in previous research, dropout from learning activities has often been interpreted as a lack of effective SRL strategies (Moreno-Marcos et al., 2020; Wild & Grassinger, 2023). However, in the context of CE, dropout should not always be considered a failure. Learners may engage in CE activities for various reasons (e.g., to learn something new, to satisfy curiosity, or to earn a certificate), not all of which require completion of the CE activity (Hemmler et al., 2023; Matcha et al., 2024). Moreover, if learners drop out of a CE activity after realizing that it has become unfeasible for their personal learning needs or that they have already achieved their personal learning goals, such behavior does not indicate failure. Rather, such behavior may be considered a manifestation of SRL (Matcha et al., 2024). In this case, ALEs should support learners in achieving their overarching learning goals rather than compelling them to persist with a CE activity that does not facilitate their advancement toward these goals.

Furthermore, given the limited effectiveness of ALEs in supporting SRL, as shown in Paper 4 of this thesis and several previous studies (Heikkinen et al., 2023; Psathas et al., 2023; Teich et al., 2024), future research should explore alternative theories to inform the design of ALEs. According to a recent systematic review on personalized dashboards conducted by Paulsen and Lindsay (2024), SRL theories may be useful for designing descriptive visualizations of individual learning behavior and for identifying individual support needs (e.g., goal setting). However, SRL theories may be inappropriate for guiding the design of concrete recommendations to assist learners based on these visualizations and support needs. In this regard, the theoretical framework should more closely align with the primary objective of the recommendation. For instance, if the primary objective is to support learners in setting learning goals, goal-setting theory could be applied. This theory provides evidence on how to establish effective goals and demonstrates how goals can enhance performance (Locke & Latham, 2002, 2019). Further, if the primary objective is to provide effective feedback to learners, the provided feedback should be aligned with theories of effective feedback (e.g., Hattie & Timperley, 2007). Moreover, as outlined in Section 7.2.1, the principles of adult learning theory (Knowles, 1980; Knowles et al., 2012) may inform the design of ALEs that align with learners' needs and experiences in CE (Wozniak, 2020). Hence, to summarize, future research may address the following research questions to explore alternative perspectives and theories on the regulation of learning:

- Are there any SRL strategies that are unique to the context of CE?
- How do learners in CE regulate their learning in contexts without explicit learning goals or standards?
- How can ALEs support the co-regulation and socially shared regulation of learning in CE?
- What are indicators of effective SRL in CE?
- How can theories apart from SRL theories inform the design of ALEs for CE?

7.4.6 Developing Ethical Guidelines

There are several ethical issues related to ALEs, such as privacy concerns, algorithmic bias, and the potential risk of aggravating inequalities (Barrera Castro et al., 2025; Klostermann & Kluy, 2025; Liu & Khalil, 2023), which were not sufficiently addressed in this thesis. Robust ethical guidelines are essential to guarantee a responsible and fair implementation of ALEs (Hemmler & Ifenthaler, 2022; Ifenthaler, 2023). For instance, clear data protection policies are needed to mitigate concerns about data privacy and misuse of learner data (Strielkowski et al., 2025). In the European Union, data collection is regulated by the General Data Protection Regulation (GDPR; European Commission, 2016), which enforces the individual's right to privacy based on the principles of transparency and choice (Nissenbaum, 2011). To comply with the GDPR, ALEs must obtain consent from learners before collecting data while being transparent about what data is collected, for what purposes it is analyzed, where it is stored, and who has access to the data (European Commission, 2016). However, research has shown that in practice, these regulations are often accomplished through lengthy and complex data collection statements that take a significant amount of time and effort to read thoroughly. Consequently, learners may passively agree to such data collection statements without reading them, rather than giving informed consent (Tsai, Perrotta, & Gašević, 2020; Tsai, Whitelock-Wainwright, & Gašević, 2020). Therefore, future research should explore more efficient ways to communicate transparency about data collection (Jones, 2019; Tsai, Perrotta, et al., 2020). To this end, future research may evaluate learners' perceptions of different data collection statements (e.g., texts, dashboards, videos) to identify the most appropriate communication techniques.

Moreover, there are concerns about whether learners agree to data collection statements of their own free will, given that disagreeing may result in them being denied access to learning opportunities (Nissenbaum, 2011; Tsai, Whitelock-Wainwright, & Gašević, 2020). Therefore, future research must generate profound insights into learners' specific privacy concerns regarding ALEs for CE. By understanding learners' privacy concerns, ALEs can be developed in a way that alleviates these concerns. For instance, ALEs should only collect indicators that learners are comfortable sharing. Paper 1 of this thesis identified several indicators of learners' internal and external conditions that ALEs for CE might collect. However, the present thesis did not evaluate the degree to which learners in CE are willing to share these indicators. Ifenthaler and Schumacher (2016) conducted a survey study to examine students' willingness to share data (e.g., name, email, user path, prior knowledge) for learning analytics systems in higher education. While the findings show that students' willingness to share data depends on the kind of data, these findings may only be applied to CE with reservations, as privacy perceptions are context-dependent (Nissenbaum, 2011). Therefore, a similar study should be conducted for the context of CE to examine which of the indicators identified in Paper 1, and under which circumstances, learners in CE are willing to share for ALEs.

Furthermore, researchers have expressed concerns about potential negative consequences related to reliability and accuracy issues of ALEs (e.g., Barrera Castro et al., 2025; Ifenthaler, 2023; Strielkowski et al., 2025). The quality of ALEs depends on the quality of the underlying data. Especially when ALEs are based on complex AI algorithms, bias in training data may introduce bias in adaptive interventions and inadvertently aggravate inequalities. For example, ALEs may disadvantage underrepresented groups of learners by providing less accurate recommendations or feedback (Baker & Hawn, 2022; Strielkowski et al., 2025). Explainable ALEs that are based on pedagogically meaningful indicators and interventions, as emphasized in the present thesis, may counteract such biases (Ifenthaler, 2023). However, additional research is needed to thoroughly evaluate the fairness of specific ALEs and to investigate the impacts of potential biases on learning processes and outcomes in CE.

Moreover, researchers have raised concerns that ALEs may exacerbate existing inequalities by favoring institutions that have the financial and technological resources to implement ALEs, while disadvantaging those with fewer resources (Barrera Castro et al., 2025; Strielkowski et al., 2025). Therefore, future research should investigate how ALEs can be effectively implemented in different sectors and how small- and medium-sized enterprises can be supported in implementing ALEs for CE. In this regard, open-source initiatives may enable cross-sector collaboration and oversight, which may facilitate control over ALEs and democratize access to such systems (Barrera Castro et al., 2025). Hence, future research may address the following research questions to address ethical issues and to develop ethical guidelines for implementing ALEs in CE:

- How should data collection statements for ALEs be communicated so that learners in CE can understand and reflect on them?
- What indicators of internal and external conditions are learners in CE willing to share for ALEs? What contextual factors influence learners' willingness to share such information?
- How do (algorithmic) biases in ALEs impact learning processes and outcomes in CE?
- How can small- and medium-sized enterprises be supported in implementing ALEs for CE?
- What barriers prevent researchers and developers from publishing software code for ALEs as open source?

7.5 Conclusion

ALEs have been widely regarded as a promising means for offering flexible and personalized CE opportunities, as well as for supporting SRL processes in today's rapidly changing society and workforce landscape (Omar et al., 2024; Teich et al., 2024). Researchers have suggested that ALEs may increase the effectiveness and efficiency of learning experiences by enhancing the fit between learner and learning activities, as well as by providing continuous opportunities for optimizing learning activities (Aleven et al., 2017; Alonso et al., 2025; Gharahighehi et al., 2024). However, ALEs for CE are still in their infancy, and their implementation encounters considerable challenges due to the limited design guidelines and empirical insights available in the context of CE (Barrera Castro et al., 2025; K. C. Li & Wong, 2023). Therefore, this thesis aimed to advance the design of ALEs for CE by generating user-centered insights and empirical evidence on ALEs and SRL in the context of CE. The thesis makes a significant contribution to the field by developing a user-centered and empirically-based design framework for selecting indicators and interventions for ALEs for CE, as well as by offering empirical insights into how different stakeholders perceive and evaluate ALEs. Moreover, this thesis provides experimental evaluations of the effectiveness of ALEs in supporting learning processes in CE and delineates under which conditions ALEs can enhance learning processes. Furthermore, this thesis contributes to the advancement of SRL theories by offering comprehensive insights into SRL processes in CE.

Overall, the findings of this thesis help to move the design of ALEs from a technologically-oriented and data-driven to a more user-centered and empirically-based perspective. While early approaches to the design of ALEs have mainly focused on technological aspects and descriptive analytics of readily available indicators (Gharahighehi et al., 2024; Ifenthaler & Yau, 2020), this thesis provides user-centered and empirical rationales for the design of ALEs. These may assist in the development of trustworthy and explainable ALEs optimized for the unique needs of learners in CE. Nevertheless, the findings of this thesis also highlight the limits of ALEs. For instance, ALEs seem to be context-dependent, and learners in CE may benefit from ALEs differently depending on their internal and external conditions. This underscores the need for comprehensive ALEs that are responsive to multiple indicators. However, developing such comprehensive ALEs that are user-friendly, trustworthy, and effective in supporting learning processes remains challenging. Moreover, as the findings of this thesis indicate, ALEs may have negative side effects when not implemented properly. Continuous negative feedback, restrictions of learner autonomy, and complex adaptation and personalization procedures may impair rather than support learning processes.

The multi-method approach adopted by this thesis represents a first step toward robust empirical evidence on ALEs and SRL in CE. However, additional research is needed to shed further light on the complex effects of ALEs on (self-regulated) learning processes in CE. Moreover, technological possibilities are constantly evolving, and educational research must keep pace with these developments. Combining technological possibilities with learning theories and robust empirical findings from educational research can provide a solid foundation for developing ALEs that effectively support learning processes (Gharahighehi et al., 2024; Plass & Pawar, 2020b). Nevertheless, ALEs may not be capable of replacing human aspects of instruction (Molenaar, 2022; Tsai, Perrotta, & Gašević, 2020), and the effective implementation of ALEs requires not only the development of effective learning systems but also the creation of conditions that enable effective learning.

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Declaration About the Use of Artificial Intelligence: During the preparation of this thesis, the author used DeepL, QuillBot Grammar Checker, and Grammarly to check for linguistic errors and improve the readability of the manuscript. After using these tools, the author reviewed and edited the content as needed and takes full responsibility for the content.

Appendix A: Additional Information on Paper 1

Table A1

Potential Learners' Evaluation of All Interventions

Prioritization score	Intervention	Total	Willingness to use	Perceived learning support	*n*
1	Adaptation of the general difficulty level and thematic focus	*M* = 6.48, *SD* = 1.02	*M* = 6.43, *SD* = 1.03	*M* = 6.52, *SD* = 1.03	21
2	Adaptive presentation of further assistance	*M* = 6.32, *SD* = 0.89	*M* = 6.37, *SD* = 0.96	*M* = 6.26, *SD* = 0.87	19
3	Continuous adjustment of the difficulty level	*M* = 6.18, *SD* = 1.03	*M* = 6.12, *SD* = 1.17	*M* = 6.24, *SD* = 0.97	17
4	Context adaptation	*M* = 6.17, *SD* = 1.28	*M* = 6.17, *SD* = 1.29	*M* = 6.17, *SD* = 1.38	18
5	Prompts for specific learning strategies	*M* = 6.16, *SD* = 0.75	*M* = 6.11, *SD* = 0.99	*M* = 6.21, *SD* = 0.63	19
6	Adaptation of the complexity	*M* = 5.95, *SD* = 1.09	*M* = 5.95, *SD* = 1.16	*M* = 5.95, *SD* = 1.20	21
7	Recommendation of learning times	*M* = 5.74, *SD* = 1.12	*M* = 5.53, *SD* = 1.28	*M* = 5.94, *SD* = 1.09	17
8	Adaptation of the learning format	*M* = 5.71, *SD* = 1.53	*M* = 5.71, *SD* = 1.61	*M* = 5.71, *SD* = 1.53	17
9	Recommendation of goal-oriented learning resources	*M* = 5.69, *SD* = 1.21	*M* = 5.67, *SD* = 1.20	*M* = 5.71, *SD* = 1.27	21
10	Recommendation of learning resources based on available time	*M* = 5.59, *SD* = 1.41	*M* = 5.75, *SD* = 1.36	*M* = 5.44, *SD* = 1.58	32
11	Adaptation to physical and mental handicaps	*M* = 5.44, *SD* = 1.41	*M* = 5.71, *SD* = 1.40	*M* = 5.18, *SD* = 1.70	17
12	Adaptation of the language or language assistance	*M* = 5.42, *SD* = 1.77	*M* = 5.42, *SD* = 1.77	*M* = 5.42, *SD* = 1.87	19
13	Presentation of activating learning resources	*M* = 5.41, *SD* = 1.39	*M* = 5.47, *SD* = 1.55	*M* = 5.35, *SD* = 1.32	17
14	Adaptation to the quality of the Internet connection	*M* = 5.40, *SD* = 1.63	*M* = 5.35, *SD* = 1.84	*M* = 5.45, *SD* = 1.54	20
15	Detection of satisfactory learning conditions	*M* = 5.39, *SD* = 1.52	*M* = 5.39, *SD* = 1.54	*M* = 5.39, *SD* = 1.54	18
16	Recommendation of learning resources relevant to the working area	*M* = 5.35, *SD* = 1.31	*M* = 5.40, *SD* = 1.43	*M* = 5.30, *SD* = 1.26	20
17	Individual countdowns	*M* = 5.33, *SD* = 1.21	*M* = 5.45, *SD* = 1.32	*M* = 5.20, *SD* = 1.47	20
18	Recommendation of learning resources based on interests	*M* = 5.31, *SD* = 1.42	*M* = 5.44, *SD* = 1.54	*M* = 5.17, *SD* = 1.58	18
19	Adaptive presentation of assistance with the digital learning system	*M* = 5.24, *SD* = 1.45	*M* = 5.35, *SD* = 1.46	*M* = 5.12, *SD* = 1.80	17
20	Adaptation of the learning duration	*M* = 5.18, *SD* = 1.59	*M* = 5.17, *SD* = 1.70	*M* = 5.19, *SD* = 1.58	32
20	Personalized feedback	*M* = 5.18, *SD* = 1.18	*M* = 5.15, *SD* = 1.31	*M* = 5.20, *SD* = 1.20	20
22	Presentation of alternative learning content	*M* = 5.16, *SD* = 1.31	*M* = 5.16, *SD* = 1.34	*M* = 5.16, *SD* = 1.42	19
23	Adaptation to device and location	*M* = 5.13, *SD* = 1.84	*M* = 5.28, *SD* = 1.91	*M* = 4.98, *SD* = 1.84	32
24	Recommendation of learning partners	*M* = 5.05, *SD* = 1.33	*M* = 5.00, *SD* = 1.38	*M* = 5.10, *SD* = 1.41	20
24	Adaptive breaks	*M* = 5.05, *SD* = 1.78	*M* = 5.14, *SD* = 1.98	*M* = 4.95, *SD* = 1.69	21
26	Emphasis of personal relevance	*M* = 4.98, *SD* = 1.53	*M* = 5.05, *SD* = 1.54	*M* = 4.90, *SD* = 1.59	20
27	Dashboards	*M* = 4.83, *SD* = 1.56	*M* = 4.67, *SD* = 1.61	*M* = 5.00, *SD* = 1.61	18
28	Adaptive group size	*M* = 4.81, *SD* = 1.57	*M* = 4.81, *SD* = 1.72	*M* = 4.81, *SD* = 1.50	21
29	Adaptation of the motivational support	*M* = 4.75, *SD* = 1.54	*M* = 4.83, *SD* = 1.50	*M* = 4.67, *SD* = 1.64	18
30	Coaching-chatbot	*M* = 4.71, *SD* = 1.57	*M* = 4.57, *SD* = 1.60	*M* = 4.86, *SD* = 1.59	21

Prioritization score	Intervention	Total	Willingness to use	Perceived learning support	*n*
31	Adaptation of the frequency of pop-ups and prompts	*M* = 4.59, *SD* = 1.61	*M* = 4.69, *SD* = 1.58	*M* = 4.50, *SD* = 1.71	16
32	Recommendation of learning resources that colleagues have completed	*M* = 4.53, *SD* = 1.54	*M* = 4.65, *SD* = 1.62	*M* = 4.41, *SD* = 1.50	17
33	Warnings in case of distraction	*M* = 4.40, *SD* = 1.89	*M* = 4.40, *SD* = 1.93	*M* = 4.40, *SD* = 1.93	20
34	Recommendation of activation/relaxation exercises	*M* = 4.34, *SD* = 1.37	*M* = 4.26, *SD* = 1.48	*M* = 4.42, *SD* = 1.43	19
35	Individual reminders	*M* = 4.33, *SD* = 1.85	*M* = 4.50, *SD* = 2.09	*M* = 4.17, *SD* = 1.95	18
36	Adaptive learning points and awards	*M* = 4.23, *SD* = 1.44	*M* = 4.25, *SD* = 1.45	*M* = 4.20, *SD* = 1.61	20
37	Adaptive learning calendar	*M* = 3.43, *SD* = 1.44	*M* = 3.35, *SD* = 1.46	*M* = 3.50, *SD* = 1.50	20

Note. Evaluation on a 7-point Likert scale: 1 = very low willingness to use/perceived learning support, 7 = very high willingness to use/perceived learning support.

Table A2

Continuing Education/Educational Technology Specialists' Evaluation of All Interventions

Prioritization score	Intervention	Total	Technological implementation effort	Organizational implementation effort	*n*
1	Individual countdowns	*M* = 1.64, *SD* = 0.75	*M* = 1.86, *SD* = 1.07	*M* = 1.43, *SD* = 0.53	7
1	Individual reminders	*M* = 1.64, *SD* = 0.48	*M* = 1.29, *SD* = 0.49	*M* = 2.00, *SD* = 0.82	7
3	Dashboards	*M* = 2.70, *SD* = 1.35	*M* = 2.60, *SD* = 1.14	*M* = 2.80, *SD* = 1.64	5
4	Adaptive learning points and awards	*M* = 2.75, *SD* = 1.07	*M* = 2.50, *SD* = 1.31	*M* = 3.00, *SD* = 1.07	8
5	Recommendation of learning resources that colleagues have completed	*M* = 2.79, *SD* = 1.11	*M* = 2.43, *SD* = 1.27	*M* = 3.14, *SD* = 1.46	7
6	Recommendation of learning resources based on available time	*M* = 2.85, *SD* = 1.51	*M* = 2.55, *SD* = 1.52	*M* = 3.15, *SD* = 1.78	10
7	Adaptation to the quality of the Internet connection	*M* = 2.92, *SD* = 0.86	*M* = 3.17, *SD* = 1.17	*M* = 2.67, *SD* = 1.03	6
8	Recommendation of learning resources relevant to the working area	*M* = 3.29, *SD* = 0.95	*M* = 2.71, *SD* = 1.11	*M* = 3.86, *SD* = 1.21	7
9	Adaptive learning calendar	*M* = 3.42, *SD* = 1.88	*M* = 3.50, *SD* = 2.17	*M* = 3.33, *SD* = 2.07	6
10	Adaptation of the language or language assistance	*M* = 3.43, *SD* = 0.98	*M* = 3.14, *SD* = 1.35	*M* = 3.71, *SD* = 0.95	7
11	Adaptive presentation of further assistance	*M* = 3.57, *SD* = 1.51	*M* = 3.43, *SD* = 1.81	*M* = 3.71, *SD* = 1.60	7
12	Recommendation of goal-oriented learning resources	*M* = 3.67, *SD* = 0.93	*M* = 3.17, *SD* = 0.98	*M* = 4.17, *SD* = 0.98	6
13	Adaptation of the motivational support	*M* = 3.75, *SD* = 1.41	*M* = 3.33, *SD* = 1.21	*M* = 4.17, *SD* = 1.72	6
14	Adaptive group size	*M* = 3.86, *SD* = 1.14	*M* = 3.29, *SD* = 1.38	*M* = 4.43, *SD* = 1.51	7
15	Adaptive presentation of assistance with the digital learning system	*M* = 4.00, *SD* = 1.78	*M* = 3.71, *SD* = 1.60	*M* = 4.29, *SD* = 2.21	7
15	Adaptive breaks	*M* = 4.00, *SD* = 0.87	*M* = 4.60, *SD* = 1.52	*M* = 3.40, *SD* = 1.34	5
17	Adaptation to device and location	*M* = 4.09, *SD* = 1.49	*M* = 4.36, *SD* = 1.69	*M* = 3.82, *SD* = 1.55	11
18	Recommendation of learning times	*M* = 4.20, *SD* = 1.60	*M* = 4.80, *SD* = 1.64	*M* = 3.60, *SD* = 1.82	5
19	Recommendation of activation/relaxation exercises	*M* = 4.21, *SD* = 1.19	*M* = 4.29, *SD* = 1.38	*M* = 4.14, *SD* = 1.57	7
20	Adaptation of the general difficulty level and thematic focus	*M* = 4.25, *SD* = 1.51	*M* = 3.67, *SD* = 2.16	*M* = 4.83, *SD* = 1.60	6
20	Adaptation of the frequency of pop-ups and prompts	*M* = 4.25, *SD* = 1.41	*M* = 4.63, *SD* = 1.92	*M* = 3.88, *SD* = 1.55	8

Prioritization score	Intervention	Total	Technological implementation effort	Organizational implementation effort	*n*
22	Personalized feedback	*M* = 4.50, *SD* = 1.87	*M* = 4.67, *SD* = 2.07	*M* = 4.33, *SD* = 1.75	6
23	Presentation of activating learning resources	*M* = 4.57, *SD* = 1.27	*M* = 4.71, *SD* = 1.50	*M* = 4.43, *SD* = 1.81	7
24	Continuous adjustment of the difficulty level	*M* = 4.58, *SD* = 1.59	*M* = 4.17, *SD* = 1.72	*M* = 5.00, *SD* = 1.67	6
24	Adaptation of the complexity	*M* = 4.64, *SD* = 1.49	*M* = 4.29, *SD* = 1.60	*M* = 5.00, *SD* = 1.41	7
24	Recommendation of learning partners	*M* = 4.64, *SD* = 1.41	*M* = 4.14, *SD* = 1.77	*M* = 5.14, *SD* = 1.57	7
24	Emphasis of personal relevance	*M* = 4.64, *SD* = 1.11	*M* = 4.29, *SD* = 1.38	*M* = 5.00, *SD* = 1.00	7
28	Context adaptation	*M* = 4.71, *SD* = 1.22	*M* = 4.29, *SD* = 1.38	*M* = 5.14, *SD* = 1.35	7
29	Detection of satisfactory learning conditions	*M* = 4.83, *SD* = 1.47	*M* = 4.83, *SD* = 1.17	*M* = 4.83, *SD* = 2.14	6
30	Prompts for specific learning strategies	*M* = 4.92, *SD* = 1.24	*M* = 4.83, *SD* = 1.83	*M* = 5.00, *SD* = 1.10	6
31	Adaptation to physical and mental handicaps	*M* = 4.94, *SD* = 1.43	*M* = 4.50, *SD* = 1.41	*M* = 5.38, *SD* = 1.60	8
32	Adaptation of the learning duration	*M* = 5.00, *SD* = 0.87	*M* = 5.12, *SD* = 1.23	*M* = 4.88, *SD* = 1.33	13
33	Adaptation of the learning format	*M* = 5.17, *SD* = 0.93	*M* = 4.67, *SD* = 1.63	*M* = 5.67, *SD* = 1.21	6
33	Warnings in case of distraction	*M* = 5.17, *SD* = 1.40	*M* = 4.67, *SD* = 1.51	*M* = 5.67, *SD* = 1.63	6
35	Recommendation of learning resources based on interests	*M* = 5.33, *SD* = 1.40	*M* = 5.00, *SD* = 1.55	*M* = 5.67, *SD* = 1.86	6
36	Presentation of alternative learning content	*M* = 5.43, *SD* = 0.93	*M* = 6.00, *SD* = 0.82	*M* = 4.86, *SD* = 1.35	7
37	Coaching-chatbot	*M* = 5.50, *SD* = 1.29	*M* = 5.57, *SD* = 1.40	*M* = 5.43, *SD* = 1.40	7

Note. Evaluation on a 7-point Likert scale: 1 = very low implementation effort, 7 = very high implementation effort.

Appendix B: Additional Information on Paper 2

Table B1

Descriptive Statistics by Condition

Variable	Condition			Total (*N* = 194)
	PSRQ (*n* = 69)	PKQ (*n* = 65)	Control (*n* = 60)	
Knowledge increase [a]	*M* = 1.38, SD = 1.72	*M* = 0.78, *SD* = 1.44	*M* = 0.32, *SD* = 2.21	*M* = 0.82, *SD* = 1.83
Learning path completion	*M* = 0.50, *SD* = 0.41	*M* = 0.52, *SD* = 0.41	*M* = 0.56, *SD* = 0.37	*M* = 0.52, *SD* = 0.40
Learner satisfaction [b]	*M* = 4.48, *SD* = 1.61	*M* = 4.80, *SD* = 1.72	*M* = 4.88, SD = 1.46	*M* = 4.73, *SD* = 1.60
Mastery GO	*M* = 6.11, *SD* = 0.69	*M* = 6.04, *SD* = 0.75	*M* = 6.00, *SD* = 0.84	*M* = 6.05, *SD* = 0.76
Performance-approach GO	*M* = 3.35, *SD* = 1.40	*M* = 3.05, *SD* = 1.51	*M* = 3.10, *SD* = 1.43	*M* = 3.17, *SD* = 1.44
Performance-avoidance GO	*M* = 2.24, *SD* = 1.25	*M* = 1.96, *SD* = 1.30	*M* = 2.05, *SD* = 1.15	*M* = 2.09, *SD* = 1.24
Work-avoidance GO	*M* = 2.68, *SD* = 1.32	*M* = 2.51, *SD* = 1.27	*M* = 2.65, *SD* = 1.28	*M* = 2.61, *SD* = 1.29
Task value	*M* = 6.23, *SD* = 0.78	*M* = 6.11, *SD* = 0.92	*M* = 6.06, *SD* = 0.82	M = 6.14, SD = 0.84
Prior knowledge	*M* = 6.30, *SD* = 2.29	*M* = 6.51, *SD* = 2.43	*M* = 6.28, *SD* = 2.58	*M* = 6.37, *SD* = 2.42
Perceived ease of use [c]	*M* = 5.86, *SD* = 1.64	*M* = 5.55, *SD* = 1.55	*M* = 5.89, *SD* = 1.16	*M* = 5.76, *SD* = 1.47
Number of skill atoms allowed to skip [d]	*M* = 6.22, *SD* = 6.43	*M* = 8.32, *SD* = 5.51	—	*M* = 7.24, *SD* = 6.07
Percentage of corrected skill atoms [e]	*M* = 0.02, *SD* = 0.10	*M* = 0.02, *SD* = 0.07	—	*M* = 0.02, *SD* = 0.08
Percentage of unnecessarily completed materials [f]	*M* = 0.05, *SD* = 0.19	*M* = 0.29, *SD* = 0.18	—	*M* = 0.17, *SD* = 0.22

Note. Knowledge increase and prior knowledge were assessed with 11 single choice items in the pre- and post-questionnaire. Knowledge increase was measured by subtracting the sum of correctly answered items in the pre-questionnaire from the sum of correctly answered items in the post-questionnaire. Prior knowledge represents the sum of correctly answered items in the pre-questionnaire. All self-reports (learner satisfaction, mastery GO, performance-approach GO, performance-avoidance GO, work-avoidance GO, task value, perceived ease of use) were measured on a 7-point Likert scale (1 = fully disagree, 7 = fully agree). PSRQ = personalization based on self-report questions, PKQ = personalization based on knowledge questions, GO = goal orientation.

[a] *N* = 108; PSRQ: *n* = 34; PKQ: *n* = 40, control: *n* = 34. [b] *N* = 111; PSRQ: *n* = 35; PKQ: *n* = 41; control: *n* = 35. [c] *N* = 110; PSRQ: *n* = 35; PKQ: *n* = 40; control: *n* = 35. [d] *N* = 134; PSRQ: *n* = 69; PKQ: *n* = 65. [e] *N* = 130; PSRQ: *n* = 66; PKQ: *n* = 64. [f] *N* = 120; PSRQ: *n* = 58; PKQ: *n* = 62.

Table B2

Correlations Between Variables

Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1. Knowledge increase	—												
2. Learning path completion	.11	—											
3. Learner satisfaction	.09	$.29^{**}$	—										
4. Mastery GO	.04	.06	.09	—									
5. Performance-approach GO	.03	.02	.16	$.15^{*}$	—								
6. Performance-avoidance GO	.15	−.03	.01	−.11	$.64^{***}$	—							
7. Work-avoidance GO	−.01	−.06	−.04	−.12	$.47^{***}$	$.68^{***}$	—						
8. Task value	.00	.02	$.17^{\dagger}$	$.54^{***}$	$.18^{*}$	−.10	−.10	—					
9. Prior knowledge	$-.35^{***}$	$.22^{**}$	.03	$.27^{***}$	−.05	$-.27^{***}$	$-.24^{***}$	$.15^{*}$	—				
10. Perceived ease of use	.10	$.34^{***}$	$.42^{***}$	.13	.06	−.07	−.03	.10	.12	—			
11. Number of skill atoms allowed to skip [a]	$-.35^{**}$	$.49^{***}$	$.27^{**}$	$.26^{**}$	.09	$-.17^{\dagger}$	$-.17^{\dagger}$	.03	$.57^{***}$	.10	—		
12. Percentage of corrected skill atoms [a]	−.00	.09	.02	−.12	.07	.01	.01	.01	.11	.06	$.15^{\dagger}$	—	
13. Percentage of unnecessarily completed materials [a]	−.01	.06	.16	−.03	−.11	−.08	−.06	.03	.04	−.09	−.03	.12	—

Note. N = 54–194. GO = goal orientation.

[a] Personalization based on self-report questions (PSRQ condition) and personalization based on knowledge questions (PKQ condition) only.

$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Appendix C: Additional Information on Paper 3

Table C1

Characteristics of Primary Studies

Author (year)	*N*	Method	SRL strategies	Associated factors	Country [a]	CE [a]	Gender [a]	Age (years) [a]
Agonács et al. (2020)	40	QN	Metacognitive self-regulation, other RMS	Achievement motivation, digital literacy, general self-regulation	Different	MOOC on Italian language and culture	39.9% female, 24.9% male, 0.6% other	*M* = 38
Alonso-Mencía et al. (2021)	11,877	QN	Critical thinking, time and study environment, composite score	Age, educational level gender, prior knowledge, CE experience, culture	Different	MOOCs on programming	23.3% female, 76.7% male	N/A
Birenbaum & Rosenau (2006) [b]	180	QN	Rehearsal, elaboration, organization, critical thinking, metacognitive self-regulation, time and study environment, effort regulation, help seeking, peer learning, composite score	Achievement motivation	Israel	In-service training for teachers	93.3% female, 0.07% male	N/A
Chaker & Impedovo (2021)	454	QN	Goal setting and planning, self-monitoring, self-evaluation and reaction, time and study environment, peer learning	Learning performance, peer interaction	N/A	MOOC on project management	55.66% female	N/A
Chen & Jang (2019)	386	QN	Goal setting and planning, self-monitoring, self-evaluation and reaction, metacognitive self-regulation	Learning performance	Taiwan	CE of secondary school teachers	68.8% female, 28.5% male, 2.8% unanswered	20–30: 6.3%, 31–40: 37.0%, 41–50: 42.1%, over 50: 14.1%, unanswered: 0.5%
Chung (2015)	441	QN	Rehearsal, elaboration, organization, critical thinking, self-monitoring, self-evaluation and reaction, metacognitive self-regulation, time and study environment, effort regulation, help seeking, peer learning, composite score	Achievement motivation	N/A	MOOCs	N/A	N/A
Cuyvers et al. (2021)	3	QL	Critical thinking, goal setting and planning, self-monitoring, self-evaluation and reaction, effort regulation, composite score	Learning performance	Belgium	CE of medical specialists	100% male	40; 37; 38

Author (year)	N	Method	SRL strategies	Associated factors	Country [a]	CE [a]	Gender [a]	Age (years) [a]
Decius et al. (2021)	702	QN	Composite score	Achievement motivation, learning performance, learner engagement, age, educational level, gender, prior knowledge, job tenure, curiosity, organizational learning culture, job demands, job involvement	Germany	CE of blue-collar workers	25.2% female, 74.8% male	16–25: 17.0%, 26–35: 19.4%, 36–45: 18.8%, 46–55: 30.3%, 56 and older: 14.4%
Fan et al. (2021)	8,788	QN	Help seeking	Learning performance	China	MOOC on flipped classrooms	61.54% female	M = 36
Fontana et al. (2015)	170	QN	Elaboration, critical thinking, goal setting and planning, self-evaluation and reaction, self-satisfaction, metacognitive self-regulation	Achievement motivation, learner engagement, job control	Different	CE in the finance industry	41.8% female, 58.2% male	M = 38.12, SD = 10.97
Geller & Bamberger (2012)	110	QN	Help seeking	Learning performance, avoidance behavior, age, gender, prior knowledge, team size, friendship relations with coworkers	Israel	CE in call centers	71% female	M = 23.8
Gijbels et al. (2012)	73	QN	Composite score	Learner engagement, organizational learning culture, job control, job demands	Belgium	CE in an information service company	27% female, 73% male	M = 36.23, SD = 7.157
Guajardo Leal (2019)	808	QN	Other CS, self-evaluation and reaction	Learner satisfaction, completion of the CE activity	N/A	Different MOOCs	33.4% female	M = 31.24, SD = 11.47
Haemer et al. (2017)	962	QN	Rehearsal, other CS, self-evaluation and reaction, help seeking	Learning performance, age, educational level, CE experience, job tenure, culture, peer interaction, learning content, working area, team size	Brazil	CE in public and private organizations	N/A	M = 36.93, SD = 9.15
Handoko et al. (2019)	643	QN	Other CS, goal setting and planning, self-evaluation and reaction, time and study environment, help seeking, composite score	Completion of the CE activity	N/A	MOOCs on digital storytelling and Web 2.0 tools	68.4% female, 29.4% male, 2.2% preferred not to say	M = 45.75, SD = 12.23
Hosseini et al. (2020)	26	QN & QL	Other CS, metacognitive self-regulation	Lack of time available for learning, flipped classroom	Iran	English as a foreign language classes	N/A	23–40
Hughes (2019)	21	QN	Metacognitive self-regulation, composite score	Completion of the CE activity	United States	Training programs for teachers	42.9% female, 57.1% male	N/A

Author (year)	*N*	Method	SRL strategies	Associated factors	Country [a]	CE [a]	Gender [a]	Age (years) [a]
Janakiraman et al. (2018)	16	QL	Self-monitoring, self-evaluation and reaction, time and study environment, peer learning	Learning performance, peer interaction, self-assessments, duration	Different	Science of happiness MOOC	N/A	N/A
Jansen et al. (2020)	1,471	QN	Goal setting and planning, self-monitoring, self-evaluation and reaction, time and study environment, effort regulation, help seeking, composite score	Learner satisfaction, SRL intervention	N/A	MOOCs on child development, clinical epidemiology, and human rights	N/A	N/A
Jo et al. (2015)	200	QN	Time and study environment	Learning performance	Korea	Commercial e-learning course on credit derivatives	73.5% female, 26.5% male	N/A
Kim et al. (2021)	664	QN	Composite score	Learner engagement, organization and structure, transactional distance	N/A	MOOC on learning	53.6% female, 46.4% male	*M* = 45.48, *SD* = 15.322
Kittel et al. (2021)	170	QN	Elaboration, goal setting and planning, metacognitive self-regulation, effort regulation, help seeking, composite score	Achievement motivation, feedback, organizational learning culture, job control, task identity	Germany /Aus-tria	CE in different organizations	50% female	*M* = 37.25, *SD* = 12.98
Kizilcec et al. (2017)	4,831	QN	Elaboration, goal setting and planning, self-evaluation and reaction, help seeking, composite score	Learner engagement, individual goal achievement, age, educational level, gender, prior knowledge, CE experience, occupation	N/A	MOOCs on Engineering, Management, Education, Transpor-tation, and Computer Science	N/A	*M* = 32.0, *SD* = 10.8
Kormos & Csizér (2014) [c]	164	QN	Metacognitive self-regulation, time and study environment, effort regulation, composite score	Achievement motivation, learner engagement, individual goal achievement	Hungary	Language courses in private language schools	62.8% female, 37.2% male	*M* = 35
Kreber et al. (2005)	31	QN	Composite score	Working area	Canada/ United States	CE of academic staff	N/A	N/A
Kyndt et al. (2014)	1,243	QN	Time and study environment	Achievement motivation, learner engagement, general self-regulation, organizational learning culture, pay satisfaction, internal employability	Belgium	CE in different organizations	55% female, 45% male	*M* = 41.88, *SD* = 11.91
Lee et al. (2020a)	291	QN	Goal setting and planning, self-monitoring, self-evaluation and reaction, time and study environment, effort regulation, help seeking, composite score	Achievement motivation, learner satisfaction	Different	MOOC on mountains	59.1% female, 40.9% male	18–25: 4.5%, 26–35: 17.2%, 36–45: 16.2%, 46–55: 15.1%, 56–65: 32.0%, over 66: 15.1%

Author (year)	*N*	Method	SRL strategies	Associated factors	Country [a]	CE [a]	Gender [a]	Age (years) [a]
Lee et al. (2020b)	184	QN	Composite score	Achievement motivation	Different	MOOCs on statistics/probability	29.3% female, 70.7% male	18–25: 32.6%, 26–35: 30.4%, 36–45: 20.7%, 46–55; 6.5%, 56–65: 7.1%, over 66: 2.7%
K. Li (2019)	4,503	QN	Goal setting and planning, time and study environment	Learning performance, learner satisfaction, age, educational level, gender, CE experience, culture	Different	MOOCs on different topics	57.09% female, 42.1% male	Under 18: 2.2%, 18–24: 11.1%, 25–34: 22.7%, 35–44: 18.7%, 45–54: 17.4%, 5–64: 16.8%, 65–74: 9.4%, 75 and older: 1.8%
Lin et al. (2018)	203	QN	Goal setting and planning, metacognitive self-regulation	Achievement motivation, learner satisfaction, ease of use, organizational learning culture, job control, job demands	China	Job training in an airline company	25.6% female, 74.4% male	*M* = 25, *SD* = 4.41
Littlejohn, Hood, et al. (2016)	362	QN & QL	Other CS, goal setting and planning, self-evaluation and reaction, self-satisfaction, time and study environment, effort regulation, help seeking	Achievement motivation, individual goal achievement, self-assessments	Different	MOOC on data science	N/A	N/A
Littlejohn, Milligan, et al. (2016)	30	QN	Other CS, self-evaluation and reaction, composite score	Achievement motivation	United Kingdom	CE of finance professionals	30.0% female, 70.0% male	*M* = 50.87, *SD* = 6.97
Lourenco & Ferreira (2019)	213	QN	Other CS, goal setting and planning, self-monitoring, self-evaluation and reaction	Achievement motivation, learning performance, learner satisfaction, organizational learning culture	Portugal	CE in different organizations	52.2% female, 48.8% male	*M* = 33.8, *SD* = 7.6
Margaryan (2019)	295	QN	Elaboration, organization, critical thinking, goal setting and planning, self-monitoring, self-evaluation and reaction, self-satisfaction, help seeking, peer learning	Working area	Different	CE of crowd workers	45.4% female, 54.6% male	18–68
Martinez-Lopez et al. (2017)	45	QN	Other CS, goal setting and planning, self-evaluation and reaction, help seeking	Age, gender	N/A	MOOCs	22% female, 71% male	15–43
Milligan & Littlejohn (2016)	35	QL	Elaboration, self-monitoring, self-evaluation and reaction, time and study environment, help seeking, peer learning	Achievement motivation, learning performance, lack of time available for learning, peer learning, online setting	Different	MOOC on clinical trials	14 female, 16 male	N/A

Author (year)	*N*	Method	SRL strategies	Associated factors	Country [a]	CE [a]	Gender [a]	Age (years) [a]
Moraes & Borges-Andrade (2015)	126	QN	Rehearsal, other CS, self-evaluation and reaction, help seeking, composite score	Learning performance	Brazil	CE of municipal officers	23.8% female, 76.2% male	*M* = 43, *SD* = 9.45
Moreno-Marcos et al. (2020)	2,035	QN	Composite score	Completion of the CE activity	N/A	MOOC on electronics	N/A	N/A
Pérez-Álvarez et al. (2020)	263	QN & QL	Organization, goal setting and planning, self-monitoring, self-valuation and reaction, time and study environment, composite score	Learning performance, learner engagement, SRL intervention	Different	MOOCs on business administration and project management	36% female, 64% male	N/A
Peters-Burton & Burtov (2017)	14	QL	Goal setting and planning, self-evaluation and reaction, effort regulation	Achievement motivation, prior knowledge, feedback	United States	Professional development course for in-service teachers	12 female	*M* = 9.6
Rabin et al. (2020)	542	QN	Other CS, goal setting and planning, self-evaluation and reaction, time and study environment, help seeking	Achievement motivation, learner satisfaction, lack of time available for learning, difficulty	N/A	English as second language MOOC	71% female	*M* = 32.4, *SD* = 11.70
Raemdonck et al. (2014)	817	QN	Composite score	Learner engagement, organizational learning culture, job control, job demands	N/A	CE of employed workers	44.2% male	*M* = 40
Rigolizzo & Zhu (2021), Study 1	511	QN	Elaboration, self-evaluation and reaction	Achievement motivation, learner engagement, Big Five personality traits, difficulty, learning content, feedback	United States	Course on facial expressions	54% male	*M* = 48, *SD* = 17
Rigolizzo & Zhu (2021), Study 3	34	QN	Elaboration	Learning performance	N/A	Course on facial expressions	56% female	*M* = 34
Schulz & Roßnagel (2010)	470	QN	Other CS, composite score	Achievement motivation, learning performance, avoidance behavior, age, CE experience, general attitudes towards learning, organizational learning culture	Germany	CE in a mail-order company	57.6% female, 42.4% male	*M* = 38.7, *SD* = 10.3
Siadaty et al. (2016)	53	QN	Other CS, goal setting and planning, self-evaluation and reaction	Learner engagement	Germany /Baltic country	CE of knowledge workers	N/A	N/A
Straka (2000)	295	QN	Composite score	Achievement motivation, job control	N/A	CE of sales administrates	26% female	41% under 40
Tang (2021)	799	QN	Composite score	Learning performance, culture	Different	MOOC on project management	N/A	N/A
Tsai et al. (2018)	126	QN	Metacognitive self-regulation	Learner engagement, learner satisfaction	Different	Chinese as a second language MOOC	71.43% female, 28.57% male	20 and below: 21.43%, 20–30: 76.98%, 31–40: 1.59%

Author (year)	*N*	Method	SRL strategies	Associated factors	Country [a]	CE [a]	Gender [a]	Age (years) [a]
van Daal et al. (2014)	95	QN	Composite score	Achievement motivation, learner engagement, avoidance behavior, gender, job tenure, Big Five personality traits, working area, hours of work	Belgium	CE of high school teachers	N/A	N/A
Vanslambrouck, Zhu, Pynoo, Thomas, et al. (2019)	16	QL	Rehearsal, organization, critical thinking, self-monitoring, time and study environment, effort regulation, peer learning	Lack of time available for learning, curiosity, learning content, online setting	Belgium	Blended courses in centers for adult education	12 female, 4 male	24–56 years
Vanslambrouck, Zhu, Pynoo, Lombaerts, et al. (2019)	213	QN	Other CS, goal setting and planning, self-evaluation and reaction, time and study environment, help seeking	Achievement motivation	Belgium	Courses in centers for adult education	70% female, 30% male	*M* = 31.31
Versuti et al. (2020)	172	QN	Critical thinking, metacognitive self-regulation, effort regulation	Working area	Brazil	Courses on teaching	Sciences Teaching Degree: 57.8% female; Extension: N/A	Sciences Teaching Degree: *M* = 38; Extension: *M* = 33
Wan et al. (2012)	212	QN	Other RMS, composite score	Achievement motivation, learning performance, learner satisfaction, digital literacy, organizational learning culture, job demands	Different	E-learning courses in an international organization	41.8% male	*M* = 27.7
Warr et al. (1999)	163	QN	Other CS, effort regulation, help seeking, other RMS	Achievement motivation, learning performance, learner engagement, learner satisfaction, age, educational level, job tenure, difficulty, organizational learning culture	N/A	Training course for technicians in motor-vehicle dealerships	100% male	*M* = 31
Warr & Bunce (1995)	106	QN	Other CS, other RMS	Achievement motivation, learning performance, learner satisfaction, age, educational level, prior knowledge, job tenure	United Kingdom	Open learning program for junior managers	93% male	*M* = 36.08, *SD* = 8.38
Wong et al. (2021), Study 2	194	QN	Goal setting and planning, self-evaluation and reaction, effort regulation	Achievement motivation, learning performance, SRL intervention	N/A	MOOCs on business, economics, and education	50.0% female, 48.5% male, 0.5% not specified, 1.0% unanswered	Under 17: 2.6%, 18–24: 23.2%, 25–34: 34.5%, 35–44: 18.6%, 45–54: 13.4%, Over 55: 6.7%

Author (year)	N	Method	SRL strategies	Associated factors	Country [a]	CE [a]	Gender [a]	Age (years) [a]
Zhu et al. (2020)	322	QN	Metacognitive self-regulation, other RMS	Achievement motivation	N/A	MOOCs on physiology, math, and English	58.1% female, 41.3% male, 0.6% not specified	N/A

Note. All self-regulated learning strategies and associated factors examined in the primary studies are presented in this table, regardless of the significance of the relationships. Presentation of descriptive statistics and the number of decimal places differ between studies, as they were reported differently across studies. Country refers to the country where the continuing education activity was carried out. QN = quantitative; QL = qualitative; SRL = self-regulated learning; CS = cognitive strategies; RMS = resource management strategies; CE = continuing education; MOOC = Massive Open Online Course. N/A = information not available.

[a] Since country, the description of the continuing education activity, as well as the gender and age distributions presented in this table, were not included in the main analyses of the paper, they were not included in the coding manual but were extracted by the first author of this paper during manuscript preparation. [b] Sample characteristics are based on the sample of in-service teachers because only this sample was included in the meta-analysis (only this sample focused on continuing education). [c] Sample characteristics are based on the sample of adult language school learners because only this sample was included in the meta-analysis (only this sample focused on continuing education).

Table C2

Results of the Three-Level Version of the Egger's Regression Test (Fernández-Castilla et al., 2021; Rodgers & Pustejovsky, 2021)

Associated Factor	b_{SE_z}	95% CI for b_{SE_z}		$t(df)$	p
		LL	UL		
Learning process-related factors					
Achievement motivation	0.31	−1.88	2.49	0.28(193)	.783
Learning performance	−3.31	−8.18	1.55	−1.36(59)	.178
Learner engagement	1.87	−1.67	5.41	1.05(77)	.297
Learner satisfaction	−1.62	−3.53	0.30	−1.73(27)	.095
Avoidance behavior	−1.36	−5.97	3.26	−0.82(4)	.461
Learner-related factors					
Age	−1.09	−4.03	1.86	−0.77(20)	.450
Educational level	−.95	−2.20	0.30	−1.60(17)	.127
Prior knowledge	−0.03	−1.25	1.19	−0.10(12)	.954
Job tenure	−0.12	−5.84	5.60	−0.05(11)	.964
CE experience	0.94	−5.47	7.36	0.31(18)	.761
Work-related factors					
Organizational learning culture	−1.44	−4.75	1.87	−0.88(37)	.384
Job control	0.88	−1.70	3.46	0.75(11)	.468
Job demands	−0.10	−8.47	8.26	−0.03(5)	.976

Note. b_{SE_z} = regression coefficients for the estimated standard error of Fisher's z; CI = confidence interval; LL = lower limit. UL = upper limit.

Figure C1

Funnel Plots of the Pooled Meta-Analyses for Learning Process-Related Factors

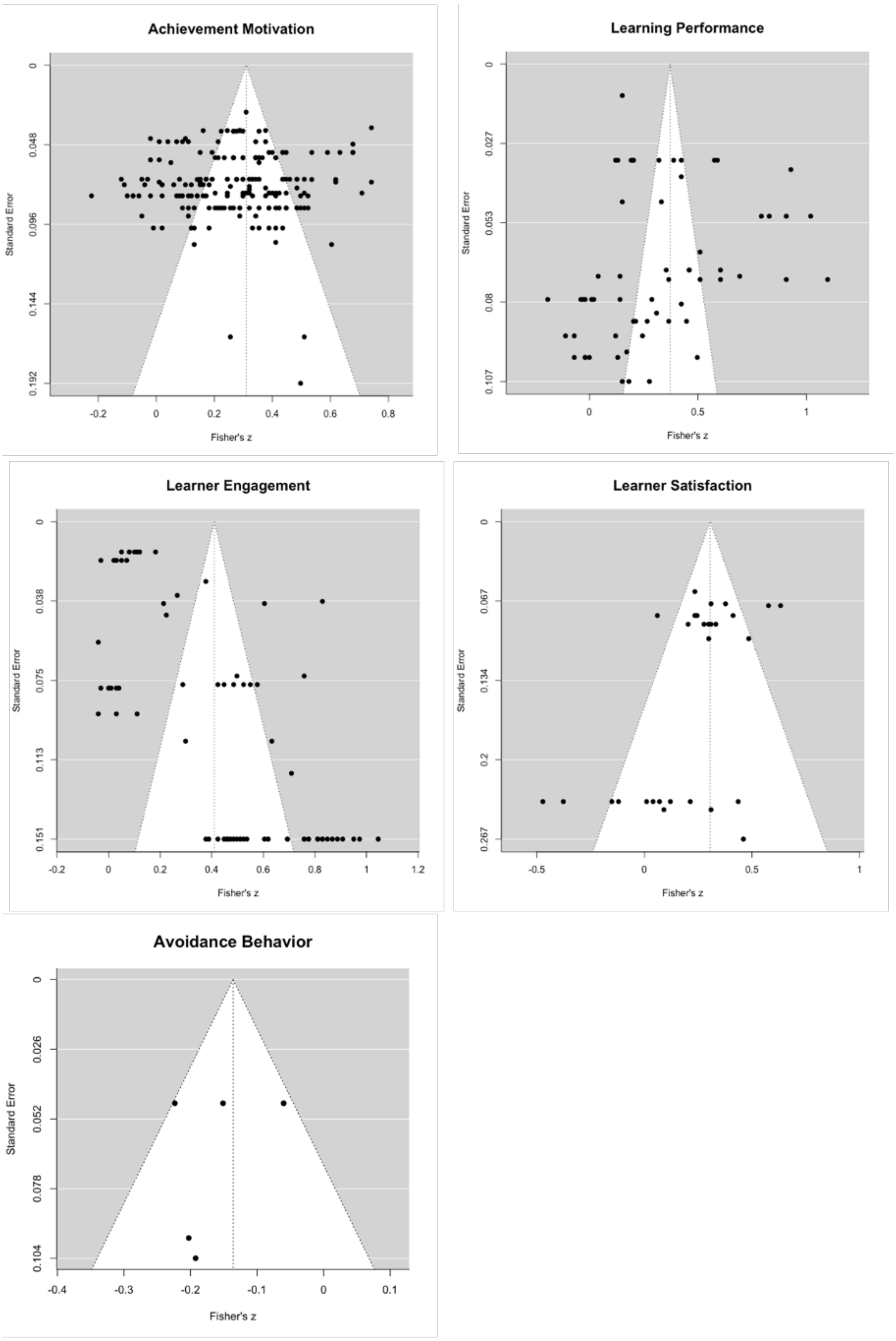
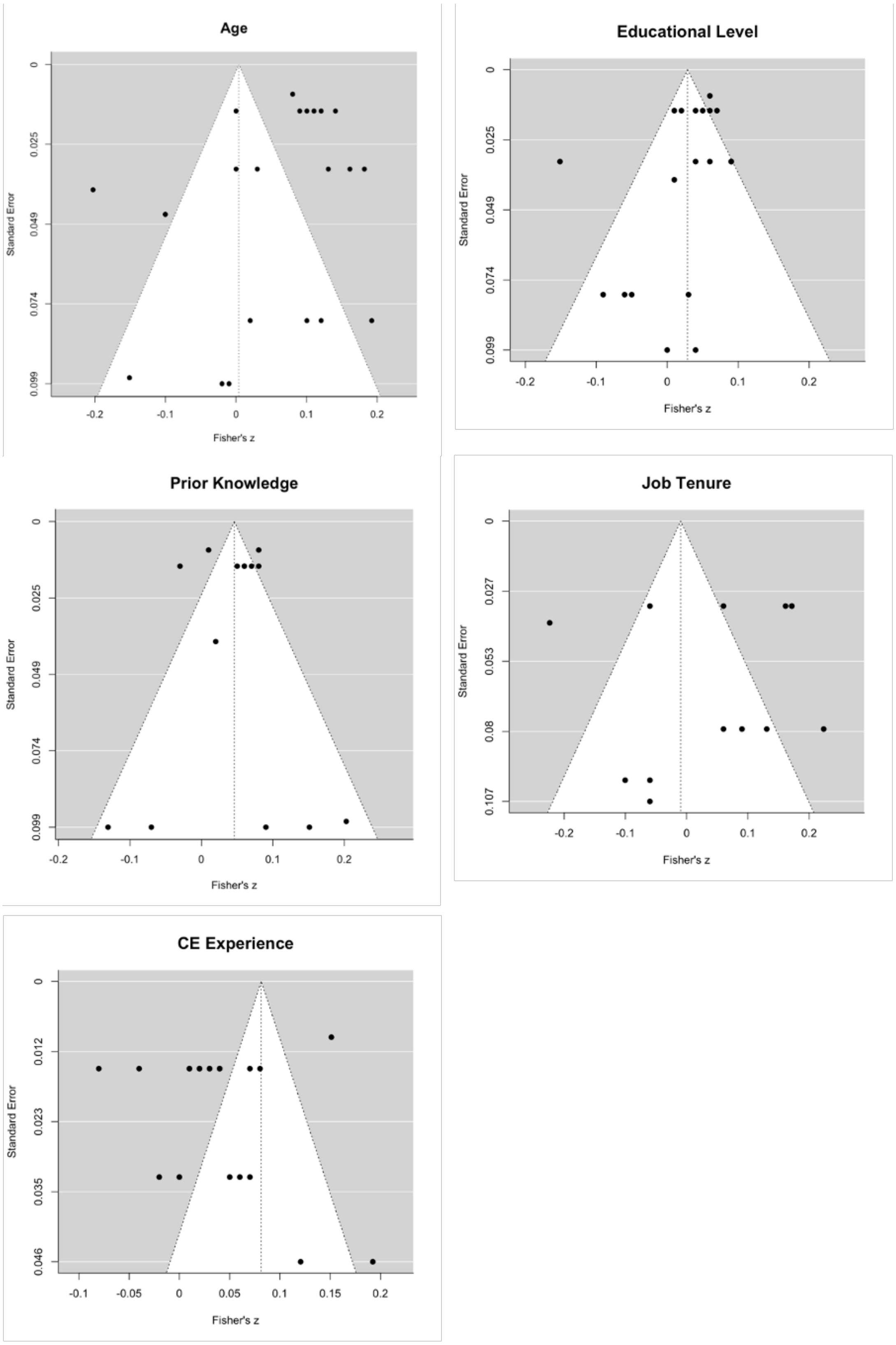


Figure C2

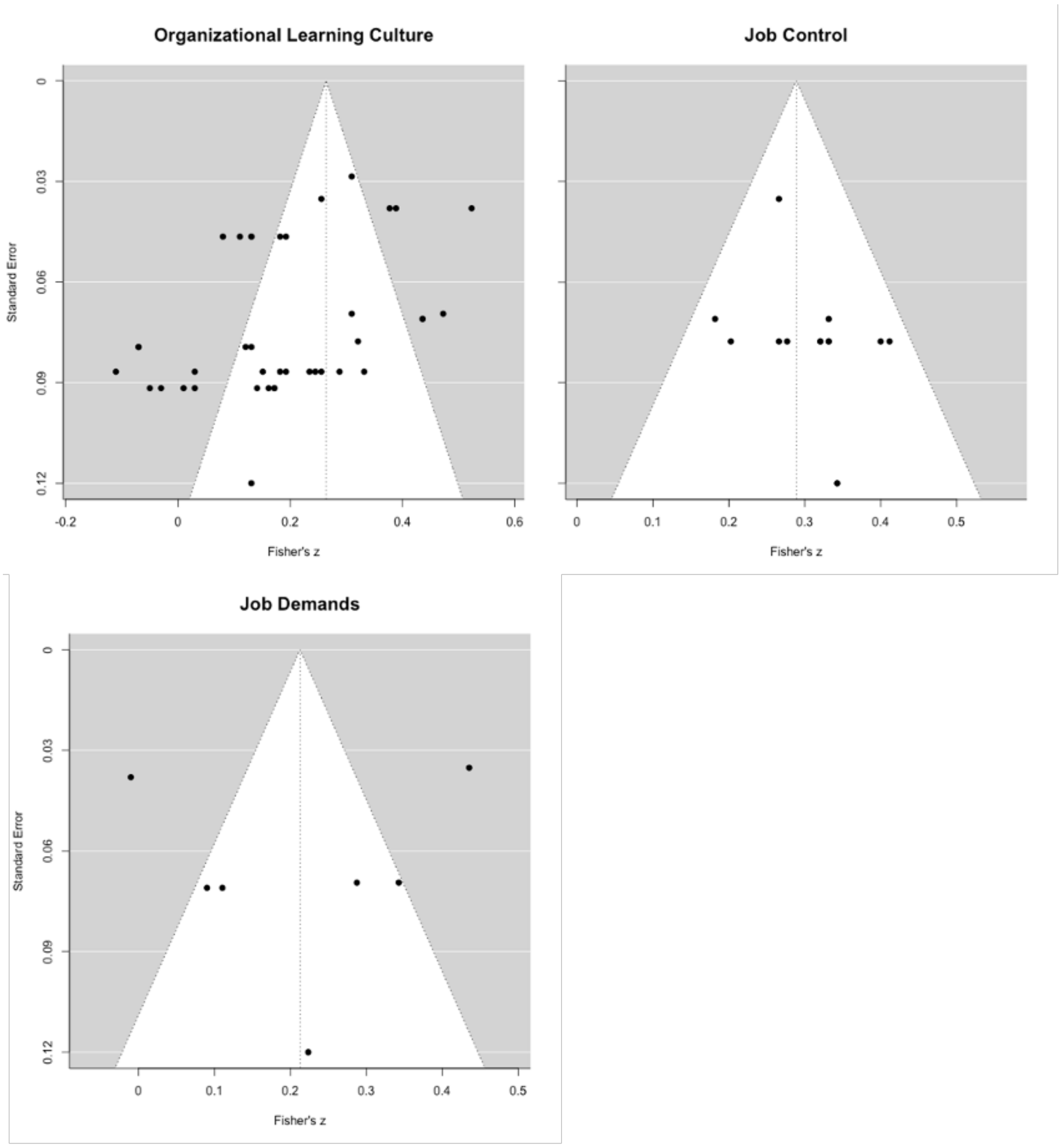
Funnel Plots of the Pooled Meta-Analyses for Learner-Related Factors



Note. CE = continuing education.

Figure C3

Funnel Plots of the Pooled Meta-Analyses for Work-Related Factors



Appendix D: Additional Information on Paper 4

Table D1

Detailed Overview of the Three Learning Paths of Study 1

Learning path	Skill atoms (approximate learning duration)	Related materials
Agile Management	1. Learning Path Guide (3 minutes)	1 text
	2. Agile Management Introduction (7 minutes)	2 videos, 1 quiz
	3. Agile and Traditional Management (15 minutes)	1 video, 1 quiz
	4. Agile Leadership (33 minutes)	2 videos, 3 quizzes
	5. Agile Meetings (28 minutes)	1 video, 2 texts, 1 quiz
	6. Agile Epics and User Stories (83 minutes)	2 videos, 3 texts, 4 quizzes
	7. Agile Transformation (24 minutes)	1 video, 1 text, 2 quizzes
	8. Agile Pro/Contra (42 minutes)	2 texts, 1 quiz
	9. Agile Management Case Studies (17 minutes)	2 texts, 2 quizzes
	10. Agile Process Steps (8 minutes)	1 text, 2 quizzes
	11. Acceptance Criteria (4 minutes)	1 video, 2 quizzes
	12. INVEST Criteria (8 minutes)	1 video, 1 quiz
	13. Magic Estimation (11 minutes)	1 video, 2 quizzes
	14. Planning Poker (8 minutes)	1 video, 1 quiz
	15. Agile and Traditional Project Management (14 minutes)	3 videos, 4 quizzes
	16. The Agile Product Management Approach (18 minutes)	1 video, 1 quiz
	17. Outlook (2 minutes)	1 text
Data Reporting	1. Learning Path Guide (3 minutes)	1 text
	2. Data Reporting vs. Data Visualization (6 minutes)	1 text, 1 quiz
	3. Data Reporting – Visual Content vs. Text (10 minutes)	1 text, 1 quiz
	4. Data in a Nutshell (12 minutes)	1 video, 1 text, 5 quizzes
	5. Introduction Storytelling (1 minute)	1 text
	6. Motivation for Storytelling with Data (49 minutes)	3 videos, 2 quizzes
	7. Discovering Stories From Data (18 minutes)	2 videos, 1 quiz
	8. The How-We-Got-Here Method (7 minutes)	1 video, 2 quizzes
	9. The Discovery Journey Method (12 minutes)	1 video, 2 quizzes
	10. Pyramid Principle (8 minutes)	2 videos, 1 quiz
	11. Introduction Design (1 minute)	1 text
	12. Design Thinking Introduction (9 minutes)	1 video, 1 quiz
	13. Gestalt Principles (13 minutes)	1 video, 3 quizzes
	14. Storytelling as a Design Tool (3 minutes)	1 video, 1 quiz
	15. Dashboard – Introduction (7 minutes)	2 videos, 1 quiz
	16. Dashboard – Fundamental Principles (5 minutes)	1 video, 1 quiz
	17. Dashboard – Defining your Audience | User Persona (5 minutes)	1 video, 1 quiz
	18. Dashboard – Consistent Design (5 minutes)	1 video, 1 quiz
	19. Pitfalls – Dashboards (6 minutes)	2 videos, 2 quizzes
	20. Introduction Visualizations (1 minute)	1 text
	21. Choosing the Tight Chart Type (26 minutes)	2 videos, 2 quizzes
	22. Data Pitfalls – Chart Rules (12 minutes)	1 video, 1 quiz
	23. Utilizing Color (33 minutes)	2 videos, 1 quiz
	24. Utilizing Text (8 minutes)	1 video, 1 quiz
	25. De-Cluttering Visualizations (7 minutes)	2 videos, 1 quiz
	26. Visual Order (5 minutes)	1 video, 2 quizzes
	27. Contrast (34 minutes)	2 videos, 1 quiz
	28. Simplicity (3 minutes)	1 video, 1 quiz
	29. Introduction Pitfalls (1 minute)	1 text
	30. Correlation vs. Causation (11 minutes)	1 video, 1 text, 3 quizzes
	31. Data Pitfalls – Bad Data Guide (5 minutes)	1 text, 1 quiz
	32. Data Pitfalls – Epistemic Errors (19 minutes)	1 video, 1 quiz
	33. Data Pitfalls – Technical Errors (15 minutes)	1 video, 1 quiz
	34. Data Pitfalls – Mathematical Errors (10 minutes)	1 video, 1 quiz
	35. Data Pitfalls – Statistical Errors (5 minutes)	1 video, 1 quiz

Learning path	Skill atoms (approximate learning duration)	Related materials
	36. Data Pitfalls – Analytical Errors (10 minutes)	1 video, 1 quiz
	37. Outlook (3 minutes)	1 text
Leadership in Practice	1. Learning Path Guide (2 minutes)	1 text
	2. Leadership vs. Management (12 minutes)	1 video, 3 texts, 4 quizzes
	3. Good Leadership – Trait or State? (29 minutes)	2 videos, 2 texts, 3 quizzes
	4. Strategy and Goals (3 minutes)	1 text
	5. Orientation and Establishing Direction (8 minutes)	1 text, 2 quizzes
	6. Strategic Goals (19 minutes)	3 texts, 1 quiz
	7. Strategic Mission (20 minutes)	1 video, 4 texts, 1 quiz
	8. Strategic Vision (14 minutes)	2 videos, 2 texts, 1 quiz
	9. OKRs – Introduction (9 minutes)	2 videos, 1 text, 3 quizzes
	10. OKRs Objectives (4 minutes)	1 video, 1 quiz
	11. OKRs Key Results (3 minutes)	1 video, 2 quizzes
	12. OKRs in Practice (51 minutes)	2 texts, 1 video
	13. Strategy Communication – Principles and Goals (5 minutes)	1 text, 1 quiz
	14. Strategy Communication – Methods (5 minutes)	1 text, 1 quiz
	15. Data (2 minutes)	1 text
	16. Why Do We Need Data Visualization? (5 minutes)	1 video, 1 quiz
	17. Data Visualization – Overview (17 minutes)	2 texts
	18. Data Literacy (13 minutes)	1 video, 1 quiz
	19. Introduction to Business Analytics (15 minutes)	1 text
	20. Agile and Innovation Management (2 minutes)	1 text
	21. Introduction to Business Model Innovation (4 minutes)	1 video, 1 quiz
	22. Agile Management Introduction (7 minutes)	2 videos, 1 quiz
	23. Agile Leadership (33 minutes)	2 videos, 3 quizzes
	24. Introduction to Intrapreneurship (13 minutes)	1 video, 1 text, 1 quiz
	25. Innovative Team Structures (15 minutes)	2 texts, 1 quiz
	26. Soft Skills (2 minutes)	1 text
	27. Empathy (19 minutes)	2 videos, 1 text, 1 quiz
	28. Motivating and Inspiring (22 minutes)	1 video, 2 quizzes
	29. Strategic Reflection (9 minutes)	3 texts, 1 quiz
	30. Active Listening Basics (3 minutes)	1 video, 1 quiz
	31. Value of Feedback (9 minutes)	2 texts, 1 quiz
	32. Feedback Mindset (25 minutes)	2 texts
	33. Giving Feedback (37 minutes)	3 videos, 2 texts, 1 quiz
	34. Common Feedback Errors (9 minutes)	1 text, 1 quiz
	35. Effective Feedback Language (15 minutes)	1 text
	36. Creating a Learning Culture (5 minutes)	1 video
	37. Self-Confidence (26 minutes)	1 video, 2 texts
	38. Rhetoric Explained (5 minutes)	1 video, 4 quizzes
	39. Change and Sustainability (2 minutes)	1 text
	40. What is Sustainable Business? (12 minutes)	2 videos, 1 quiz
	41. What is Corporate Social Responsibility? (14 minutes)	1 video, 1 text, 1 quiz
	42. Corporate Social Responsibility vs. Sustainability (2 minutes)	1 text, 1 quiz
	43. Diversity Management (2 minutes)	1 text
	44. Ethical Leadership (7 minutes)	1 video, 1 text, 1 quiz
	45. What is DEI? (6 minutes)	1 text, 1 quiz
	46. What is Diversity Management? (11 minutes)	1 video, 2 texts, 1 quiz
	47. The Rising Importance of Diversity Management (7 minutes)	1 text
	48. Components of a Diversity Strategy (6 minutes)	1 text, 1 quiz
	49. Implementing a Diversity Strategy (36 minutes)	4 texts
	50. Outlook (3 minutes)	2 texts

Note. Learning materials 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 learning duration of a skill atom is the sum of the learning durations assigned to the related learning materials. The Agile Management and Leadership in Practice learning paths were offered in German. The titles of the skill atoms were translated into English to present them in this table. The Data Reporting learning path was offered in English.

Table D2

Descriptive Statistics and Correlations Among Variables (Study 1)

Variable	*M*	*SD*	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1. Metacognitive self-regulation (pre)	4.94	0.84	—									
2. Metacognitive self-regulation (post)	4.52	0.98	.47***	—								
3. Time and study environment (pre)	4.54	1.03	.54***	.23*	—							
4. Time and study environment (post)	4.76	1.15	.16	.27*	.47***	—						
5. Percentage of completed learning materials [a]	0.67	0.39	−.02	.07	.22**	.50***	—					
6. Overall learning goal [a, b]	—	—	−.13	.06	.11	.11	−.01	—				
7. Sum of dashboard accesses [a]	1.82	3.91	.01	.24	.04	.13	.31**	.19	—			
8. Sum of goal modifications [a]	0.18	0.56	.08	.16	−.10	−.10	.22†	.13	.64***	—		
9. Percentage of achieved weekly goals [a]	0.33	0.36	−.10	−.05	.20	.63***	.64***	.36**	.25*	.10	—	
10. Total number of active days	5.21	4.44	−.02	.04	.07	.14	.41***	−.01	.31**	.31**	.20†	—

Note. $N = 46–146$. The variable *sum of goal abandonments* was not included in the correlation table due to limited variance.
[a] Intervention condition only. [b] 63 out of 73 participants in the intervention condition set an overall learning goal.
$^{\dagger}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table D3

Think-Aloud Tasks and Reflective Questions Defined in the Interview Guide (Study 2)

Task/question	Text	Context
	Main part	
Task 0a	"Please describe what you can see on the starting page. Do you notice anything in particular?"	Platform
Task 0b	"Please open the learning path Learning and Development Technology and describe what you can see. Do you notice anything in particular?"	Platform
Task 1a	"Please set the learning path Learning and Development Technology as your learning goal."	Platform
Task 1b	"There is the possibility to open a dashboard that provides detailed visualizations of your learning goal. Do you have an idea where to open this dashboard?"	Platform
Task 1c	"Please complete the first learning material of the learning path Learning and Development Technology."	Platform
Task 1d	"Please open the dashboard again and describe what you can see."	Platform
Task 1e	"Please complete the assessment element of the personalization system."	Platform
Task 1f	"Please open the dashboard again and describe what you can see."	Platform
Task 1g	"Please update the deadline of your learning goal."	Platform
Task 1h	"Please open the dashboard again and describe what you can see."	Platform
Task 1i	"Please go back to the starting page and check your learning goal."	Platform
Task 2a	"Please describe what you see."	Screenshot "On track, last week's goal achieved" [a]
Task 2b	"Please describe what you see."	Screenshot "On track, last week's goal not achieved" [a]
Task 2c	"Please describe what you see."	Screenshot "At risk, last week's goal not achieved" [a]
Task 2d	"Please describe what you see."	Screenshot "At risk, last week's goal achieved" [a]
Task 2e	"Please describe what you see."	Screenshot "Overdue" [a]
Task 2f	"Please describe what you see."	Screenshot "Completed" [a]
	Reflection part	
Reflection 0	"What is your first impression of the intervention?"	—
Reflection 1	"To what extent do you think the intervention could support the forethought phase of your learning process?" [b]	—
Reflection 2	"To what extent do you think the intervention could support the performance phase of your learning process?" [b]	—
Reflection 3	"To what extent do you think the intervention could support the self-reflection phase of your learning process?" [b]	—

Note. The interviews were conducted in German. The interview questions were translated into English to present them in this table.
[a] See Figure 6-6. [b] Participants were given a definition of the forethought, performance, and self-reflection phase according to Zimmerman's (2000) model of SRL.

Table D4

Coding Manual (Study 2)

Main Category	Code	Subcode	Explanation	Task/question	Sample quotations
Salience	Starting page – first glance	Yes	The participant notices the intervention on the starting page directly after logging in.	Task 0a	—
		No	The participant does not notice the intervention on the starting page after logging in.	Task 0a	
	Starting page – after interaction	Yes	The participant notices the intervention on the starting page after interacting with it in the learning path overview.	Task 1i	—
		No	The participant does not notice the intervention on the starting page after interacting with it in the learning path overview.	Task 1i	—
	Learning path overview – first glance	Yes	The participant notices the intervention directly after opening the learning path overview.	Task 0b	—
		No	The participant does not notice the intervention after opening the learning path overview.	Task 0b	—
	Learning path overview– setting overall learning goal	Yes	When prompted to do so, the participant finds the button to set a goal in the learning path overview.	Task 1a	—
		No	The participant does not find the button to set a goal in the learning path overview.	Task 1a	—
	Learning path overview – dashboard	Yes	When prompted to do so, the participant finds out how to open the personalized dashboard.	Task 1b	—
		No	The participant does not figure out how to open the personalized dashboard.	Task 1b	—
	Learning path overview – updating deadline	Yes	When prompted to do so, the participant figures out how to update the deadline.	Task 1g	—
		No	The participant does not figure out how to update the deadline.	Task 1g	—
Understanda-bility	Overall learning goal	Yes	The participant understands the principles of the goal-setting functionality (i.e., that an overall learning goal consists of a learning path and a deadline, and how the average weekly learning time is calculated).	Task 1a Task 1g	"I can set a deadline. I see that it takes a lot of time. I would choose June 16, then, I only have to learn around 20 minutes per week" (Interview 2).
		No	The participant does not understand the principles of the goal-setting functionality or is confused.	Task 1a Task 1g	—
	Dashboard – general	Yes	In general, the participant understands the visualizations in the dashboard (overall progress, weekly goal, details).	Task 1a Task 1b Task 1g Task 2a–f Reflection 0	"I can see how many days remain until the deadline and that I am on track […] I can see my weekly goal and compare my performance from the last week to what is planned for the next week" (Interview 10)
		No	In general, the participant does not understand the general visualizations in the dashboard (overall progress, weekly goal, details) or is confused.	Task 1a Task 1b Task 1g Task 2a–f Reflection 0	"I can see that I no longer have to study this week" [screenshot 'On track, last week's goal achieved'] (Interview 20).

Main Category	Code	Subcode	Explanation	Task/question	Sample quotations
	Dashboard – after completion of learning materials	Yes	The participant understands the changes in the dashboard visualizations after completing learning materials.	Task 1c Task 1d	"Now, I have already completed 4%, and I still have the same deadline" (Interview 1).
		No	The participant does not understand the changes in the dashboard visualizations after completing learning materials or is confused.	Task 1c Task 1d	"Now, I have already completed 4 out of 40 minutes. I'm a bit confused because it did not take me 4 minutes" (Interview 13).
	Dashboard – after personalization	Yes	The participant understands the changes in the dashboard visualizations after completing an assessment element of the learning path personalization system.	Task 1e Task 1f	"I can see that the number of completed atoms has increased" (Interview 5).
		No	The participant does not understand the changes in the dashboard visualizations after completing an assessment element of the learning path personalization system, or is confused.	Task 1e Task 1f	"Now, I have 3 out of 50 minutes. Previously, I had 3 out of 55 minutes. That surprises me because I have not completed more minutes, but the minutes decreased" (Interview 7).
	Dashboard – after updating deadline	Yes	The participant understands the changes in the dashboard visualizations after updating the deadline.	Task 1g Task 1h	"Now, I have more time to complete the learning path because I postponed the deadline" (Interview 4).
		No	The participant does not understand the changes in the dashboard visualizations after updating the deadline, or is confused.	Task 1g Task 1h	—
Design	Clarity	Positive aspects	Positive comments on the clarity of the intervention.	Entire interview	"The dashboard is clearly arranged" (Interview 1).
		Negative aspects	Negative comments on the clarity of the intervention.	Entire interview	"I think that I would understand it faster if this hourglass and the text 'You need to catch up. Your goal is at risk!' were the heading" (Interview 9).
	Colors	Positive aspects	Positive comments on the colors of the intervention.	Entire interview	"I like the colors, that it is blue in the beginning, green in the end, yellow if my goal is at risk, and red if I failed" (Interview 1).
		Negative aspects	Negative comments on the colors of the intervention.	Entire interview	"The color is not that striking. If I'm on track, this is great. And here, it is very small and blue. It could be more colorful" (Interview 7).
	Emojis	Positive aspects	Positive comments on the emojis in the dashboard.	Entire interview	"The emojis are cute" (Interview 2).
		Negative aspects	Negative comments on the emojis in the dashboard.	Entire interview	"This rocket here […] I don't know what it is supposed to mean" (Interview 5)
	Text	Positive aspects	Positive comments on the text elements of the intervention.	Entire interview	"I like this motivating message" (Interview 19).
		Negative aspects	Negative comments on the text elements of the intervention.	Entire interview	"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)
Goal setting and planning	Realistic time and effort estimation	—	The intervention helps develop a realistic idea about the time and effort needed to complete the learning path.	Entire interview	"When selecting a learning path, I think that it may help me get an idea about how much time it will take" (Interview 1).
	Learning plan	—	The intervention helps create a learning plan and organize learning to reach the overall learning goal.	Entire interview	"It helps to organize my learning" (Interview 7).

Main Category	Code	Subcode	Explanation	Task/question	Sample quotations
	Specific recommendations to set realistic goals are needed	—	The intervention should provide more support to set realistic goals. Intervention should provide recommendations or warn the learner if the selected deadline is too optimistic.	Entire interview	"Maybe in the beginning, the system could give a recommendation for an ideal average weekly learning time […] Otherwise, you might be too ambitious with your deadline" (Interview 15).
	Missing planning autonomy	—	The participant would like more autonomy in planning the weekly goals. Intervention is too prescriptive in terms of time allocation and does not consider individual appointments (e.g., vacations).	Entire interview	"You should also be able to pause the system […] if you are on vacation, for example" (Interview 11).
	No planning of learning content	—	The intervention does not help plan learning content (only time aspects).	Entire interview	"I do not see the planned learning content" (Interview 8).
	Learning goals should be based on learning tasks and content	—	The overall learning goal that can be set is not meaningful. Meaningful learning goals should be based on learning tasks and content rather than learning time.	Entire interview	"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	Monitoring of learning progress	—	The intervention is useful for monitoring one's progress within the learning path.	Entire interview	"The bar helps me get an overview of my current status" (Interview 1).
	No monitoring of learning content	—	The intervention does not help monitor one's understanding of the learning content.	Entire interview	"I cannot monitor how much I know already" (Interview 7).
	Motivation to surface learning	—	The intervention may motivate learners to quickly click through the learning content in order to see progress in the dashboard rather than engaging with the learning content deeply.	Entire interview	"It may not motivate me to engage with the learning content deeply but to click through as much content as possible" (Interview 7).
Self-evaluation and reaction	Developing an idea about one's weekly time resources	—	The intervention helps develop a realistic idea about one's weekly time resources.	Entire interview	"It may help me get an idea about how much time I can study each week" (Interview 1).
	Possibility to change the deadline	—	The participant appreciates the possibility to change the deadline in order to adapt learning processes if needed.	Entire interview	"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).
	Missing recommendations for adapting the deadline	—	The intervention misses specific recommendations for adapting deadlines. Intervention should motivate to change the deadline if the overall learning goal becomes unreachable and should provide recommendations for a realistic deadline.	Entire interview	"Maybe some hints or a mouseover effect that shows what would change if you selected another deadline" (Interview 6).
	Missing summary on weekly goals	—	The intervention should not only show the previous week's, the current week's, and the following week's goal. The participant would like to get a summary of all previous weeks.	Entire interview	"I would like to have a complete overview of my past progress […] I get a review of my last week, but if I have already learned several weeks, I cannot reflect on what happened before" (Interview 14).
	No reflection on learning content	—	The intervention does not help reflect on learning content.	Entire interview	"I cannot reflect on the learning content, only on the time aspects" (Interview 6).

Main Category	Code	Subcode	Explanation	Task/question	Sample quotations
Time and study environment	Scheduling learning time	—	The intervention helps schedule learning times and balance learning with other commitments.	Entire interview	"It helps me take time for learning and schedule learning times" (Interview 20).
	Monitoring learning time	—	The intervention helps understand whether one is on track or not and whether one has to invest more time in learning in the next weeks.	Entire interview	"The remaining time helps me get a feeling about how much I still need to do" (Interview 1).
	Missing calendar integration	—	The intervention misses a direct connection to a calendar to schedule learning times and plan other appointments.	Entire interview	"Maybe, I would need a calendar to schedule my learning times" (Interview 16).
	Missing reminder	—	The intervention misses a reminder for learning.	Entire interview	"That you get a reminder if you have not finished your workload by the end of the week" (Interview 12)
	Weekly feedback is too unspecific	—	The participant would like to get more detailed feedback on the learning progress (e.g., specific indications of how many minutes need to be caught up).	Entire interview	"The feedback that you are on track or that your goal is at risk is too unspecific for me" (Interview 2).
	Missing specific support if weekly goals are not achieved	—	The intervention does not help explore the reasons for not achieving weekly goals. The participant would like to get more detailed support if a weekly goal is not achieved.	Entire interview	"Maybe some recommendations for common problems or reasons for not achieving your goal" (Interview 6).
Effort regulation	Commitment	—	The intervention enhances commitment towards the learning path.	Entire interview	"It creates commitment" (Interview 1).
	Small steps	—	The intervention enhances motivation by breaking the learning path into small steps.	Entire interview	"It is motivating because it breaks the overall learning path into chunks that are easier to manage" (Interview 7).
	Seeing progress	—	The intervention enhances motivation by visualizing one's progress.	Entire interview	"It enhances my motivation because it says that I have made great progress" (Interview 2).
	Motivation for further learning paths	—	Once the overall learning goal is achieved, the intervention may motivate the completion of further learning paths/continuing education activities.	Entire interview	"If I achieved my goal, […] this might motivate me to complete another learning path" (Interview 5).
	Demotivating if the overall learning goal is at risk	—	If the overall learning goal is at risk, the intervention creates stress, decreases motivation, and may cause dropout.	Entire interview	"If you are not on track and the weekly goals increase continuously, this creates a bad feeling […] The workload might become too heavy, and you might stop" (Interview 15).
	Missing motivation through learning content	—	The participant would prefer to be motivated through the learning content of the learning path rather than time aspects.	Entire interview	"I would prefer to see the learning tasks rather than the minutes" (Interview 7).
	More gamification needed	—	The participant would appreciate more gamification elements.	Entire interview	"On other learning platforms, you can earn badges. I do not see this here" (Interview 10).

Note. Interviews were conducted in German. The sample quotations were translated into English to present them in this table.

Online Supplemental Materials

The online supplemental materials of Paper 1 and Paper 3 can be accessed via the online version of the paper:

- Paper 1: https://doi.org/10.1016/j.chbr.2024.100525
- Paper 3: https://doi.org/10.1016/j.edurev.2024.100629

Clicking on the following links will automatically download the documents (Microsoft Excel files) from the journal website:

- Paper 1: Interview guides and coding manuals of Study 1 and Study 2: https://ars.els-cdn.com/content/image/1-s2.0-S2451958824001581-mmc1.xlsx
- Paper 3: Detailed description of the effect sizes included in the meta-analyses: https://ars.els-cdn.com/content/image/1-s2.0-S1747938X24000381-mmc1.xlsx

Curriculum Vitae

Professional Appointment

Since 2021	Research Assistant, Economic and Business Education – Learning, Design and Technology, Business School, University of Mannheim, Germany

Academic Education

2021	Master of Science, Psychology: Economic, Organizational and Social Psychology, Ludwig-Maximilians-Universität München, Germany
2018	Bachelor of Science, Psychology, Ludwig-Maximilians-Universität München, Germany
2017	Semester abroad, Université de Montréal, Canada

Teaching Activities

Since 2024	Analysis of Research Data / Empirical Research Methods (undergraduate level, German, fall) Educational Management / Digitally Supported Learning Culture (undergraduate level, German, spring)
Since 2021	Supervising bachelor's and master's theses
2022 – 2024	Empirical Instructional Research (graduate level, German, spring)

Memberships

AERA, AECT