

Scaffolding Self-Regulated Learning with Advanced Learning Technologies

Laying the Groundwork and Testing Effects of Personalized Scaffolds

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Vollständiger Abdruck der von der TUM School of Social Sciences and Technology der Technischen Universität München zur Erlangung des akademischen Grades einer **Doktorin der Philosophie (Dr. phil.)** genehmigten Dissertation.

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Die Dissertation wurde am 18.11.2022 bei der Technischen Universität München eingereicht und durch die TUM School of Social Sciences and Technology am 06.03.2023 angenommen.

For my dearest Prince, Hayley, and Oscar

Acknowledgements

I would like to extend my sincerest gratitude to the people who have supported me both in a professional and personal capacity in my doctoral journey.

First and foremost, I would like to thank my esteemed supervisor, Prof. Dr. Maria Bannert, for being the best supervisor anyone could ask for. Without her continued support, this dissertation would not have been possible. I greatly appreciate all the opportunities she provided me and all the times she looked out for my well-being over the last few years. Ich danke dir von ganzem Herzen, Maria, dass du immer an mich geglaubt hast und mich inspirierst, eine bessere Forscherin zu werden.

I truly appreciate and thank the FLoRA project team and collaborators for the valuable discussions, support, and feedback, which tremendously shaped my academic journey.

I would also like to thank Prof. Dr. Tina Seidel and Prof. Roger Azevedo, Ph.D., who kindly agreed to serve on the examination committee to review this dissertation and additionally, Prof. Dr. Jenna Koenen for chairing the examination committee.

I would like to acknowledge the (anonymous) reviewers who provided me constructive feedback to improve my work.

A big thank you to my wonderful colleagues and friends at the Chair for Teaching and Learning with Digital Media at TUM for their incredible support, continuous encouragement, and helpful discussions. Working with all of you has been such a great pleasure! I would also like to acknowledge the support from my fellow doctoral candidates and friends, Laura, Sabrina, and Steffen, whom I have had the chance to work with in the last years and who lent a listening ear whenever I needed it. A special thank you goes out to Kerstin and Elena, who were the OGs with me in our newbies group.

Thank you to all my friends for believing in me and encouraging me.

Last but not least, I would like to thank my beloved family for their unwavering support and encouragement. My deepest gratitude goes to my parents for always believing in me and letting me forge my own path. A special thanks goes out to my favorite sister who is always there for me. And to my favorite aunts, Xiao Yi and Er Yi, thank you.

Abstract

Self-Regulated Learning (SRL) is key to lifelong learning and is well linked to improved learning outcomes. Yet, students do not always regulate their learning well and may engage in sub-optimal SRL, especially in digital and online learning settings. Scaffolding different SRL activities has been found in prior studies to improve students' learning. However, it can be a challenge to directly implement recommendations from previous studies due to how well findings can be generalized across different learning tasks and contexts owing to varying approaches used. There is potential in incorporating advanced learning technologies to scaffold SRL given the stark increase in digital and online learning. For scaffolds to optimally support learning, they need to both adapt to students' learning progress as well as personalized to individual learning needs. Against this backdrop, this dissertation aims to progress SRL support with advanced learning technologies. There were three action steps which were taken in the work presented in the dissertation. The first action step focused on the measurement and analyses of SRL as groundwork for the next step. Building upon this, the second action step was to develop and improve SRL support. Finally, the last action step involved the testing of personalized scaffolds.

The first study focused on extending prior research by providing insights into which findings were generalizable to a new learning task and context. A pre-post design laboratory study was conducted with 29 university students. SRL was measured through concurrent think aloud protocols and coded with an adapted coding scheme from prior research. The results showed metacognitive activities to be related to transfer performance, consistent with past studies. Through the comparison of successful and less successful students' SRL activities and by modelling their SRL patterns, results largely coherent with past research were found; successful students engaged in more metacognitive, especially monitoring, and deep cognitive activities, reflecting more similarities with SRL proposed by theory. In addition, the results indicated that successful students integrated specific activities, like rereading, strategically in their repertoire of activities, in comparison to less successful students who performed the same activities, albeit at a lower frequency, but struggled to connect them well during learning. Planning and evaluation activities were found to occur rarely, regardless of how successful students' learning was.

The second study focused on the implementation and testing of analytics-based personalized scaffolds based on students' real-time learning activities. Using a pre-post between-subject experiment, students who received personalized scaffolds ($n = 35$) were

compared with students who received generalized scaffolds ($n = 30$) and no scaffolds ($n = 29$), in terms of effects on learning activities, learning outcomes, and temporal structure of SRL activities. Personalized scaffolds were found to influence learning activities the most, yet learning performance differences were absent. Large similarities were found in process models illustrating the temporal structures of learning activities, which potentially explained the missing learning outcome effects. As in the first study, planning and evaluation activities were found to occur infrequently, suggesting a need to reassess how they should be supported. Additionally, process model comparisons indicated that students who received no support were able to engage in spontaneous regulation of learning, providing follow-up research opportunities such as whether structured learning environments with embedded learning tools already support SRL activities and how increased proficiency in usage of learning and scaffold tools (e.g., personalized scaffolds) could lead to learning outcome effects.

Overall, this dissertation contributes with insights to further development of SRL support using advanced learning technologies as well as suggestions for theory development. The dissertation highlights the importance of the deeper investigation into learning processes through both measurement and analysis approaches and provides greater understanding to the implementation and effects of adaptive and personalized SRL support.

Zusammenfassung

Selbstreguliertes Lernen (SRL) ist der Schlüssel zu lebenslangem Lernen und steht in engem Zusammenhang mit besseren Lernergebnissen. Lernende haben jedoch Schwierigkeiten ihr Lernen zu regulieren, was sich oftmals im defizitären SRL widerspiegelt. Dies gilt insbesondere für das Lernen in digitalen und Online-Lernumgebungen. Studien konnten belegen, dass das Lernen der Studierenden durch Scaffolding verschiedener SRL-Aktivitäten verbessert werden kann. Die Vielzahl bestehender Ansätze bisheriger Forschung erschwert die direkte Umsetzung von Empfehlungen und Generalisierung auf verschiedene Lernaufgaben und -kontexte. Angesichts der starken Zunahme des digitalen und Online-Lernens besteht ein großes Potenzial zur Förderung des SRL in fortschrittlichen Lerntechnologien. Damit Scaffolds das Lernen optimal unterstützen können, müssen diese sowohl an den Lernfortschritt der Lernenden angepasst werden als auch auf die individuellen Lernbedürfnisse abgestimmt sein. Vor diesem Hintergrund zielt diese Dissertation darauf ab, die Unterstützung des SRL durch fortschrittliche Lerntechnologien voranzutreiben. Im Rahmen der in der Dissertation vorgestellten Arbeit wurden drei Handlungsschritte unternommen. Der erste Handlungsschritt konzentrierte sich auf die Messung und Analyse des SRL als Grundlage für den nächsten Schritt. Darauf aufbauend bestand der zweite Handlungsschritt aus der Entwicklung und Verbesserung der Unterstützung des SRL. Der letzte Handlungsschritt schließlich umfasste die Erprobung von personalisierten Scaffolds.

Die erste Studie konzentrierte sich auf die Erweiterung früherer Forschungen, indem Erkenntnisse darüber geliefert wurden, welche Ergebnisse auf eine neue Lernaufgabe und -kontext übertragen werden können. Es wurde eine Laborstudie im Pre-Post Design mit 29 Studierenden durchgeführt. SRL wurde mit Hilfe von Protokollen zum Lauten Denken gemessen und mit einem angepassten Kodierschema aus früheren Studien kodiert. Übereinstimmend mit vorherigen Studien zeigten die Ergebnisse, dass metakognitive Aktivitäten mit der Transferleistung in Zusammenhang stehen. Mit Hilfe des Vergleichs der SRL-Aktivitäten erfolgreicher und weniger erfolgreicher Studierender und der Modellierung der SRL-Muster konnten Ergebnisse gefunden werden, die weitgehend mit früheren Untersuchungen übereinstimmen; erfolgreiche Studierende führten mehr metakognitive, insbesondere überwachende, und tiefgehende kognitive Aktivitäten durch. Dies spiegelt sich auch in der Theorie des SRL wieder. Darüber hinaus deuteten die Ergebnisse darauf hin, dass erfolgreiche Studierende bestimmte Aktivitäten, wie z. B. wiederholtes Lesen, strategisch in ihr Aktivitätsrepertoire integrierten. Im Gegensatz dazu hatten weniger erfolgreiche

Studierende, die dieselben Aktivitäten, wenn auch in geringerer Häufigkeit, durchführten, Schwierigkeiten diese während des Lernens gut zu verknüpfen. Es wurde festgestellt, dass unabhängig vom Lernerfolg Planungs- und Evaluierungsaktivitäten nur selten vorkamen.

Die zweite Studie konzentrierte sich auf die Implementierung und Erprobung von Analyse basierten personalisierten Scaffolds auf der Grundlage der Echtzeit-Lernaktivitäten der Studierenden. Anhand eines pre-post between-subject Experiments wurden Studierende, die personalisierte Scaffolds ($n = 35$) erhielten, mit Studierenden verglichen, die generalisierte Scaffolds ($n = 30$) oder keine Scaffolds ($n = 29$) erhielten, und zwar hinsichtlich der Auswirkungen auf die Lernaktivitäten, die Lernergebnisse und die zeitliche Struktur der SRL-Aktivitäten. Es stellte sich heraus, dass personalisierte Scaffolds die Lernaktivitäten am stärksten beeinflussten, während es keine Unterschiede in der Lernleistung gab. Es wurden große Ähnlichkeiten in den Prozessmodellen gefunden, die die zeitlichen Strukturen der Lernaktivitäten veranschaulichen, was möglicherweise die fehlenden Auswirkungen auf die Lernergebnisse erklärt. Wie bereits in der ersten Studie festgestellt wurde, kamen Planungs- und Bewertungsaktivitäten nur selten vor. Dies deutet darauf hin, dass die Form der Unterstützung neu bewertet werden muss. Darüber hinaus zeigten Prozessmodellvergleiche, dass Studierende, die keine Unterstützung erhielten, in der Lage waren, spontane Lernregulation vorzunehmen. Dies bietet Möglichkeiten für Folgeuntersuchungen, z. B. zu der Frage, ob strukturierte Lernumgebungen mit eingebetteten Lernhilfen bereits SRL-Aktivitäten unterstützen und wie eine erhöhte Kompetenz bei der Nutzung von Lernhilfen und Scaffolds (z. B. personalisierte Scaffolds) zu Effekten in den Lernergebnissen führen könnte.

Zusammengefasst trägt diese Dissertation mit ihren Erkenntnissen zur weiteren Entwicklung der Unterstützung des SRL durch fortschrittliche Lerntechnologien bei und gibt Anregungen für weitere theoretische Ausarbeitungen. Die Dissertation unterstreicht die Bedeutung einer tiefgreifenderen Untersuchung von Lernprozessen durch Mess- und Analyseansätze und liefert ein besseres Verständnis für die Implementierung und Auswirkungen adaptiver und personalisierter Unterstützung des SRL.

Included Publications

The present dissertation includes two papers published in international peer-reviewed journals. The author of this dissertation led as first author in both papers as well as played a major role in the conceptualization and design of the studies, development of instruments, materials, and scaffolds, data collection, coding, and analyses, and writing of the manuscripts and revisions. The co-authors in the publications supported in their capacity as team members and principal investigators of the international and interdisciplinary project, which the studies of this dissertation were embedded in. All authors provided critical reviews to the manuscripts and revisions as well as read and approved the submitted versions. The details of the main contributions of each co-author are as follow: Dr. Joep van der Graaf co-developed the instruments and materials, and scaffolding model. Dr. Yizhou Fan developed the trace-based process library and co-developed the scaffolding model. Dr. Shaveen Singh co-developed the learning environment and the scaffolding model. Dr. Mladen Rakovic supported the development of the rule-based AI system and the manuscript revisions. Jonathan Kilgour and Surya Surendrannair provided technical expertise in the development of the learning environment and the scaffolding model. Prof. Dragan Gašević, Prof. Inge Molenaar, and Prof. Johanna Moore were the principal investigators of the project as well as contributed to the manuscript reviews and revisions. The supervisor, Prof. Maria Bannert, was the main principal investigator of the project and guided the conceptualization and design of the studies, and reviewed the manuscripts and revisions.

The first publication was submitted to the international peer-reviewed, open-access journal, “Frontiers in Psychology” (Research Topic: Self-Regulated Learning in Online Settings), in July 2021 and accepted for publication in November 2021 (see Appendix A).

Lim, L., Bannert, M., van der Graaf, J., Molenaar, I., Fan, Y., Kilgour, J., Moore, J., & Gašević, D. (2021). Temporal Assessment of Self-Regulated Learning by Mining Students’ Think Aloud Protocols. *Frontiers in Psychology, 12*:749749.
<https://doi.org/10.3389/fpsyg.2021.749749>

The second publication was submitted to the international peer-reviewed journal, “Computers in Human Behavior” (Special Issue: Advancing SRL Research with AI), in March 2022 and accepted for publication in October 2022 (see Appendix B).

Lim, L., Bannert, M., van der Graaf, J., Singh, S., Fan, Y., Surendrannair, S., Rakovic, M., Molenaar, I., Moore, J., & Gašević, D. (2023). Effects of real-time analytics-based personalized scaffolds on students’ self-regulated learning. *Computers in Human Behavior, 139*, 107547.
<https://doi.org/10.1016/j.chb.2022.107547> (published online on 27.10.2022)

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1 Introduction

In order to engage in and sustain productive lifelong learning in different settings, one needs to have the competency to regulate one's learning, also known as self-regulated learning (SRL; Boekaerts, 1999; European Union, 2019). The need to regulate one's learning well becomes more pronounced in digital and online learning settings as learning materials, tasks, tools, and support are often embedded and learners have to independently steer their learning, making multiple decisions on how to learn and complete the tasks. Examples of digital and online learning settings include, massive open online courses (e.g., Pérez-Álvarez et al., 2018), learning management systems (e.g., Moodle, Cerezo et al., 2020), open-ended learning environments (e.g., Poitras et al., 2021), intelligent tutoring systems (e.g., Azevedo et al., 2022), hypermedia learning environments (e.g., Bannert, 2004), public professional development platforms (e.g., Seidel et al., 2020) and so forth. There has been an exponential surge in learning taking place in these settings particularly due to the COVID-19 pandemic, when online learning was one of the main learning modes available (EDUCAUSE, 2021). How one regulates their learning, also in online settings, correlates with their learning success (Broadbent & Poon, 2015; Schunk & Greene, 2017); being able to regulate skillfully, especially during exceptionally challenging times like the pandemic when students additionally suffer from multiple other challenges (e.g., anxiety), can facilitate learning success (Hadwin et al., 2022). However, students most often face difficulties in the spontaneous regulation of their learning (Flavell et al., 1966; Veenman et al., 2005) and the issue is compounded by engagement in sub-par regulation strategies in digital and online learning settings (Azevedo & Feyzi-Behnagh, 2011).

Scaffolding has been used to support learners to internalize and independently perform skills which they previously could not do without support (Reiser & Tabak, 2014; Wood et al., 1976). This is also applicable in SRL and scaffolding different SRL activities have been empirically shown to improve learning outcomes (Guo, 2022; Zheng, 2016) though there have also been studies which demonstrated mixed success and require deeper investigation (e.g., Bannert & Reimann, 2012; Pieger & Bannert, 2018; Reid et al., 2017; Van den Boom et al., 2004). Scaffolds, implemented as embedded prompts in digital and online learning environments, have been used widely in prior studies (e.g., Bannert et al., 2014; Bannert & Reimann, 2012; Moos & Bonde, 2016; Wong et al., 2021) to stimulate use of SRL skills and knowledge during learning. However, there have been various challenges acknowledged in research with regards to designing and implementing SRL scaffolds, such

as, what, when, and how to scaffold learners (Bannert, 2009; Thillmann et al., 2009; Wirth, 2009), as well as how learners utilize the support provided (i.e., compliance, Bannert & Mengelkamp, 2013; Bannert & Reimann, 2012; Engelmann et al., 2021; Jansen et al., 2020; Lallé et al., 2017; Moser et al., 2017).

SRL is a dynamic and complex process, whereby activities and processes are adapted as learners regulate their learning (Azevedo, Moos, et al., 2010; Winne, 2010). Current theoretical models largely conceptualize SRL to be a cyclical and weakly sequenced process made up of three main phases with distinctive macro- and micro-level activities (e.g., Panadero, 2017; Puustinen & Pulkkinen, 2001; Winne & Hadwin, 1998; Zimmerman, 2000). Given the nature of SRL and individual learning needs, this also means that scaffolds which serve to facilitate SRL need to be fundamentally adaptive and also personalized. Scaffolds adjust and fade support provided based on students' learning progress which is continuously monitored (Puntambekar & Hubscher, 2005) and support can be personalized to each learner by differentiating the content of support provided (Pardo et al., 2019). Therefore, there are two chronological components that make up scaffolds which optimally support learning. First, there needs to be an accurate representation of students' actual learning progress, i.e., how learning is captured and what the recorded data reflect in terms of SRL activities. Second, dependent on the information gathered from students' learning behavior, there needs to be consideration in terms of whether support is needed, what activity needs to be supported, and how the support is differentiated for each learner.

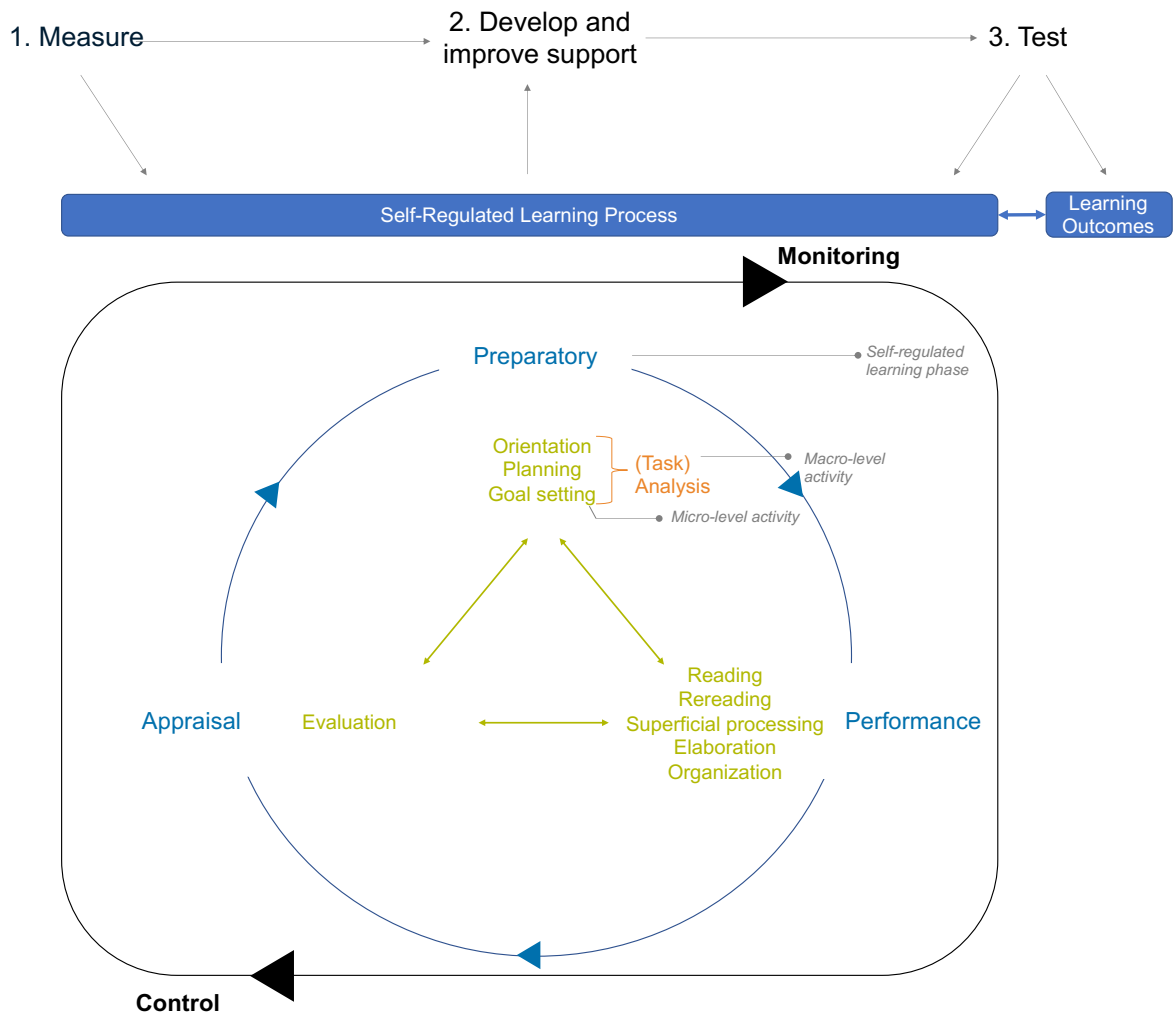
With that in mind, the research presented in this dissertation sought to address two main objectives with three key action steps. Figure 1 visualizes the theoretical underpinnings of the current dissertation along with the action steps. The first aim of the dissertation is to extend prior research and promote a deeper understanding of SRL (i.e., action step one) as groundwork for the development and improvement of SRL scaffolds (i.e., action step two). Specifically, the first action step was the measurement of SRL, i.e., measurement approach, which tied in with the modality of measurement (e.g., think aloud protocols), the granularity of learning activities captured and subsequently analyzed, as well as consistency with previous findings. The second action step involved the development and improvement of SRL scaffolds based on theory and analyses of students' SRL behavior from earlier studies (study 1, L. Lim et al., 2021; van der Graaf et al., 2022). The second aim of the dissertation is to implement and empirically test advanced SRL interventions (i.e., action step three). This involved the development and implementation of a rule-based artificial intelligence (AI) system which integrated real-time SRL measurement and personalized SRL support in an

online learning environment. Overall, the dissertation aims to contribute by providing insights to the use and effects of advanced learning technologies in supporting SRL, to further optimize advanced SRL support, as well as providing suggestions for theory development.

In the overview of the dissertation in the following sections, the empirical studies are framed to a more general context. The overview of the dissertation is structured as follows: The first section (Section 2) of the overview introduces the SRL theoretical framework used in the research in this dissertation. Then, the next section (Section 3) discusses the measurement and (temporal) analyses of SRL using the event-based perspective. The subsequent section (Section 4) goes into detail about scaffolding SRL with a focus on (sufficiently) adaptive and personalized scaffolds as well as a review on the current adaptive scaffolds used in SRL research. Next, the aims of the present research are introduced (Section 5; i.e., laying the groundwork for the development and improvement of SRL scaffolds, implement and empirically test advanced SRL interventions) followed by the methodology approach (Section 6) used to address the research aims. Following that, a summary of both studies is presented (Section 7). Finally, the main findings and implications from both studies are discussed and suggestions for theoretical development are proposed (Section 8). The last section (Section 9) concludes the dissertation.

Figure 1

The dissertation framework



2 Theoretical Framework of Self-Regulated Learning

A learner's individual regulation comprises of a set of loosely sequenced time-ordered regulatory activities (e.g., Winne & Hadwin, 1998; Zimmerman, 2000). A learner regulates their learning by actively monitoring and controlling the metacognitive and cognitive activities they engage in to pursue their goals (Pintrich, 2000). There are three common cyclical phases which can be identified across different SRL models, such as the Winne and Hadwin's (1998) COPES model, Zimmerman's (2000) social cognitive cyclical model of SRL, Pintrich's (2000) SRL model which also adopted a social cognitive perspective, and Boekaerts' (2011) Dual Processing model, namely, the preparatory, performance, and appraisal phases (Panadero, 2017; Puustinen & Pulkkinen, 2001). In each of the SRL phases, distinct macro- and micro-level activities can be identified. Macro-level activities have been defined in past research as the aggregate of specific micro-level activities and are often indicative of an SRL phase. For example, in Zimmerman's SRL model, goal setting and strategic planning fall in the macro-level category of task analysis—a key activity in the forethought phase of the model. Azevedo and colleagues (2008) differentiated five micro-level processes, planning, goals, prior knowledge activation, and recycle goal in working memory, in the macro-level category of planning. Siadaty and colleagues (2016b) categorized task analysis, goal setting, and making personal plans, as micro-level SRL processes which fall into the broader macro-level category of planning. In Bannert et al.'s (2014) work, SRL activities were first coded into micro-level categories (e.g., planning, orientation, goal setting) and subsequently aggregated to broader macro-level categories (e.g., analysis). The examples illustrate that micro-level SRL activities can show slight variations depending on the learning tasks and contexts. Nevertheless, the broader category of macro-level activities from past studies remained highly indicative of the main SRL phases despite varying contextual nature of learning tasks. Therefore, SRL activities which are characteristic of each phase can still be identified. The next paragraph goes into detail of each SRL phase and the representative micro-level activities.

In the preparatory phase of SRL, as the name implies, learners prepare for learning by analyzing the task through orientation activities, set goals for their learning, and plan their learning as guided by their goals (Pintrich, 2000; Zimmerman, 2000). Hence, typical micro-level activities in the preparatory phase can be categorized as orientation, planning, and goal setting. In the performance phase, learners execute the task by implementing cognitive strategies and also monitoring and controlling the processing of learning content and the

operations they apply to the processing of content (Winne, 2019). In this phase, cognitive strategies can be characterized as high cognitive (also commonly known as deep processing) or low cognitive (also commonly known as superficial or surface processing). Low cognitive activities are activities learners engage in when they process the learning content in a shallow manner in order to take note of important information; the information processed are retained in the working memory (Weinstein & Mayer, 1983). These activities include forming a knowledge base through (first) reading of learning materials (Frey et al., 2017) and rehearsal strategies such as repeating (aloud), rereading, and copying (verbatim) (Weinstein & Mayer, 1983). High cognitive activities facilitate learners to process information in a deeper manner and include elaboration and organization strategies (Weinstein & Mayer, 1983). Elaboration strategies comprise of paraphrasing, explaining, and connecting new information to prior knowledge, etc. Learners use organization strategies, such as outlining and organizing their learning, so as to identify main ideas and connect these ideas. Micro-level cognitive activities in this phase can therefore be categorized as (first) reading, rereading, repeating or superficial processing, elaboration, and organization. In the appraisal phase, learners reflect on and evaluate their learning based on pre-defined goals and standards (Zimmerman, 2000). Based on the appraisal of their learning, they then adapt their SRL for their next learning cycle. Thus, a typical micro-level activity in the appraisal phase is evaluation. Finally, based on theoretical conceptions of metacognition, such as the Nelson and Narens (1994) conceptualization of cognition, and the elaborated Winne and Hadwin (1998) COPES model, metacognitive activities, especially monitoring, which occur at the “meta-level”, influence control activities, which occur at the “object-level”. The object-level in turn informs the meta-level. An example is one’s judgments of learning influencing one’s decision to take notes (i.e., new action), continue to reread parts of a text (i.e., continue the action) or stop reading (i.e., terminate action). Therefore, monitoring is a micro-level activity that is ubiquitous across all SRL phases. SRL occurs in a cyclical manner and there is a general temporal sequence suggested by SRL models, but learning activities do not have to occur in a strict linear order; SRL activities at the micro-level can switch between SRL phases (Azevedo, 2009). Hence, in order to capture the dynamic nature of SRL, it is important to consider how it is measured and analyzed. This also reflects the first focus of the current dissertation which is elaborated in the next section.

3 Measuring and Analyzing Self-Regulated Learning

Processes

Approaches to measuring and analyzing SRL have adopted one of two perspectives, i.e., aptitude and event, in past and current SRL research (Reimann, 2009; Reimann et al., 2014; Winne & Perry, 2000). The perspective adopted also determines if measurements of SRL are taken online (i.e., during learning) or offline (i.e., before or after learning) (Veenman, 2013). The first perspective views SRL as an aptitude and measurement approaches include self-report questionnaires (e.g., Motivated Strategies for Learning Questionnaire, Pintrich et al., 1993) and structured interviews (e.g., Self-Regulated Learning Interview Schedule, Zimmerman & Pons, 1986) (Winne & Perry, 2000). The second perspective considers SRL as an event and measurement methods include think aloud protocols (e.g., Bannert, 2007; Greene & Azevedo, 2009), trace and peripheral data consisting of logfiles, mouse movements, keystrokes, eye gaze data (e.g., Bernacki et al., 2012; Hörmann & Bannert, 2016; Kinnunen & Vauras, 2010), and micro-analyses (e.g., Cleary & Callan, 2017). Although approaches using either an aptitude- or an event-based perspective measure SRL, they do not measure the same aspects. When a researcher administers aptitude-based perspective measurements, for example, self-report questionnaires, they are interested to investigate global aspects of SRL with the assumption that the variable(s) in question is acting upon the outcome variable(s) throughout learning (Reimann, 2009). These measures are typically taken offline and depend on the learner's self-reports (Veenman, 2013). On the other hand, when a researcher employs event-based measurement methods, for example, think aloud protocols recorded during learning, they are interested to (directly) observe actual SRL behavior (Reimann et al., 2014). Such SRL measurements are taken online and focus on process data through behavior (e.g., trace data) and verbalizations (e.g., concurrent think aloud protocols) (Veenman, 2013). Research in SRL has progressively shifted to conceptualizing SRL as an event and using the corresponding measurement and analysis methods, e.g., think aloud protocols and temporal analysis (Bannert et al., 2014; Molenaar, 2014; Reimann, 2009; Reimann et al., 2014; Winne & Perry, 2000) largely due to the poor calibration of aptitude-based measures, such as self-report questionnaires, with actual learning behavior (Bannert & Mengelkamp, 2013; Veenman, 2016). In contrast, event-based online measures not only correlate with other online measures more but are also strong predictors of performance (Veenman, 2013, 2016),

potentially due to the finer grained nature of these measures which focus on SRL strategies used during learning (Rovers et al., 2019).

Linked to the earlier section (Section 2), current SRL theories suggest that SRL occurs dynamically in relation to sequence, namely, from preparatory to performance to appraisal phase, and time, such as how micro-level SRL activities during learning could transition to and from different phases (i.e., not strictly ordered) and how SRL activities relate to each other over time; furthermore, learning strategies change over time due to learners adapting their learning as they progress (e.g., Winne & Hadwin, 1998). Researchers in the field of SRL have emphasized the need to investigate the temporal and sequential characteristics of SRL further, through both suitable measurement and analysis approaches, to consolidate understanding of how to support SRL better (Järvelä & Bannert, 2021; Molenaar & Järvelä, 2014). To that end, the studies in the current dissertation focused on two specific event-based online measurement approaches, i.e., concurrent think aloud and analytics-based measurement protocol, and additionally, the use of process analysis methods, i.e., process mining, to understand and lay the groundwork for SRL support. The following two sub-sections (Sections 3.1 and 3.2) elaborate on each of the measurement approaches and the final sub-section (Section 3.3) focuses on the process mining analysis approach.

3.1 The concurrent think aloud approach

Concurrent think aloud (CTA) has been preferred over self-report questionnaires in previous SRL research which focus on SRL process (e.g., Bannert et al., 2014; Greene & Azevedo, 2009) due to greater insights into how SRL activities unfold and how SRL is linked to students' learning achievements (Greene et al., 2010). According to Ericsson and Simon (1984), during CTA, students do not interpret or judge what they verbalize but rather, verbalize every thought out loud as is. At the same time, the authors also highlighted that students may need additional processing time due to verbal encoding and longer periods of silence could indicate high cognitive load at the moment or the high automaticity of the activity being performed. However, it is important to note that there are three levels of verbalizations, namely, talk aloud (level 1), think aloud (CTA; level 2), and reflect when prompted (level 3) (Ericsson & Simon, 1984). Bannert and Mengelkamp (2008) conducted experiments testing both CTA (level 2) and reflect when prompted (level 3) approaches against a control group. They reported no learning performance differences between the CTA and control group, which provided empirical evidence to suggest that CTA is a nonreactive method. They also found that using the reflect when prompted approach could influence

performance. Using CTA brings about many advantages, such as allowing researchers to observe learning without altering the processing of information (Winne, 2018) and is a valid approach to reveal SRL processes (Greene et al., 2018; Veenman, 2013). Think aloud protocols collected during learning are a form of event-based data that allows the dynamic nature of SRL processing to be modeled, hence, it is especially suited for the observation of SRL processes, particularly when coded with detailed coding schemes derived from theory (Greene et al., 2018; Reimann et al., 2014). However, think aloud protocols are coded *post hoc* and moreover, the coding process is very laborious, thus it is not suitable for just-in-time SRL support and real-time measurement and analysis of SRL. Nevertheless, using CTA to observe SRL can lead to a better understanding of how SRL occurs and findings advance development of improved interventions.

3.2 Analytics-based measurement protocol: A Self-Regulated Learning measurement approach using trace data

Trace (also termed peripheral) data are digital traces of a learner's interaction with technology such as a technologically-enhanced learning environment and are event-based (Bernacki, 2017; Hörmann & Bannert, 2016). Examples of trace events which are typically collected are navigational logs, mouse movements, keystrokes, eye gaze points which are logged with information about when the event occurred (i.e., timestamp), where the event occurred (e.g., learner on page 1 of text), and what exactly happened (e.g., learner created a note on page 1) (Bernacki, 2017; Hörmann & Bannert, 2016). Researchers can unobtrusively observe systematic patterns in learning behavior through the traces learners generate while learning, particularly so when the behavior is made traceable, e.g., via learning and instrumentation tools, in the learning environment (van der Graaf et al., 2021; Winne, 2010). However, interpreting learning behavior from traces can be a challenge since traces do not provide information about the reasons behind the observed behavior, making validity a prominent issue when working with this data type (Bernacki, 2017; Winne, 2020). To tackle validity issues, researchers have combined theory-and-data-driven approaches using think aloud data as a reference point to develop and improve analytics-based SRL protocols (see Fan, van der Graaf, et al., 2022). Analytics-based SRL measurement protocols use fine-grained trace data and analytic methods for the extraction of SRL processes (e.g., Fan, van der Graaf, et al., 2022; Gašević, Jovanovic, et al., 2017; Siadaty et al., 2016b). They differ from coarser-grained simple navigation logs, which, alone, do not measure students' ongoing learning reliably (Järvelä & Bannert, 2021). In addition to measurement, the analytics-based

approach can be used to personalize SRL support. Pardo et al. (2019) and L.A-Lim et al. (2021) both implemented algorithm-based customization of feedback content which dynamically analyzed students' trace data (i.e., analytics-based measurement) to provide personalized feedback at scale in university courses. Azevedo and Gašević (2019) pointed out several challenges when dealing with multimodal and multichannel data, various forms of trace data inclusive, namely, the temporal alignment due to differing sampling rates, data quantity and granularity in order to categorize and interpret learning processes correctly, the underlying complexities in each data stream as well as theoretical framework(s), among other challenges. Nonetheless, one of the biggest advantages of using trace data to measure SRL, especially through analytics-based measurement protocols, is that the data can be collected and processed in real-time and consequently used as instantaneous input to real-time SRL support interventions, paving the way for the use of suitable artificial intelligence methods to further improve and extend SRL measurement and support.

3.3 Using process mining to investigate Self-Regulated Learning processes

The above approaches focus on an event-based perspective of detecting SRL processes and similarly provide the means for investigating the temporality and sequentiality of SRL, which could extend our understanding of SRL beyond learning outcomes (Roll & Winne, 2015). Researchers in the field of SRL have increasingly utilized process analysis approaches, such as process and sequence mining, t-pattern analysis, lag sequential analysis, statistical discourse analysis, etc., to investigate how SRL develops and unfolds over time (Molenaar & Järvelä, 2014), in order to increase explanatory power (Molenaar, 2014; Reimann, 2009). Previous empirical studies have modelled SRL via process-level data, such as, think aloud and trace data, and found evidence distinguishing the main SRL phases, especially in successful students' learning and students supported by metacognitive prompts, as well as in large student samples (e.g., Bannert et al., 2014; Cerezo et al., 2020; Huang & Lajoie, 2021; Maldonado-Mahauad et al., 2018; Sonnenberg & Bannert, 2015; Wong et al., 2019). Furthermore, past studies have investigated the temporal and sequential structure of students' SRL with respect to why and how SRL scaffolds worked (or did not work) in order to understand the effects of scaffolds on the learning process (Engelmann & Bannert, 2019; Hsu et al., 2017; Sonnenberg & Bannert, 2015). The studies in this dissertation focus on the process mining approach, which is used to gain deeper insights into the temporal structures of learners' SRL (Bannert et al., 2014) and focus on modeling learning patterns (Romero &

Ventura, 2013). Hence, this dissertation first attempted to replicate the results of previous findings (i.e., Bannert et al., 2014) in the first study, in particular, by looking at SRL processes and the resulting temporal structures of more and less successful students to identify SRL strengths and deficits for the purpose of developing better SRL interventions. Then, in the second study, the effects of SRL intervention on the SRL process were investigated. In both studies, process discovery algorithms (i.e., Study 1: Fuzzy Miner and Study 2: First Order Markov Models) were implemented.

4 Scaffolding Self-Regulated Learning Processes

Consistent findings in previous research regarding the link of certain SRL activities in improving learning outcomes have been found, suggesting that some specific SRL processes are dependably beneficial across learning tasks and contexts (Bannert & Mengelkamp, 2013; Moos & Miller, 2015; Müller & Seufert, 2018). Metacognitive activities, in particular, have been linked with the increase in the use of deep learning strategies (e.g., higher quality of organization processes, Roelle et al., 2017) and help to deepen understanding (Bannert et al., 2009; Deekens et al., 2018). Thus, SRL, and especially metacognitive activities, have also been found to correspond to better learning performance in transfer tasks where learners have to apply their knowledge and skills to new situations (Bannert & Mengelkamp, 2013; Müller & Seufert, 2018; Schunk & Greene, 2017). Furthermore, findings like the work from Sonnenberg and Bannert (2015) provided empirical evidence behind the mechanism driving better transfer performance; results from their study showed that the number of monitoring activities mediated transfer performance to a larger extent, when compared to the number of all metacognitive activities. Several studies have also found that successful learning was characterized by more strategic SRL (Bannert et al., 2014; L. Lim et al., 2021; Paans et al., 2019). Yet, learners oftentimes struggle with spontaneously regulating their learning—a phenomenon termed production deficit (Flavell et al., 1966; Veenman et al., 2005). Learners additionally engage in less-than-ideal SRL in advanced digital learning settings, such as poorly adapting learning behavior and the use of ineffective learning strategies, which do not facilitate learning in an optimal way, also known as dysregulated learning (Azevedo & Feyzi-Behnagh, 2011).

Scaffolding different SRL activities has been found to lead to improved learning outcomes, which is particularly evident in transfer performance (Bannert et al., 2015; Bannert & Mengelkamp, 2013; Guo, 2022; Lin & Lehman, 1999; Müller & Seufert, 2018; Zheng, 2016). Scaffolding has been conventionally facilitated by a human tutor with instructional tools and strategies, in order to bridge the gap between what learners are able and unable to do without support (Reiser & Tabak, 2014), with the end goal of learners being able to internalize the necessary skills so they can perform them independently (Wood et al., 1976). Scaffolds have been implemented in digital learning environments as hints, tools, questions, prompts, pedagogical agents or intelligent tutors, and feedback (Harley et al., 2018; Molenaar & Chiu, 2014; Puntambekar & Hubscher, 2005; Roll et al., 2006; Zheng, 2016). Prompts, in particular, have been extensively used in previous SRL studies (Zheng, 2016). Prompts act as

short-term interventions to trigger the execution of SRL skills and knowledge (Bannert, 2009) with the basic assumption that learners, especially at the tertiary education level, have the necessary competencies to regulate their learning but face difficulties doing so spontaneously (Veenman, 2016; Veenman et al., 2006). However, findings from studies with SRL scaffold interventions, such as prompts, have shown mixed success (Azevedo, Johnson, et al., 2010; Bannert et al., 2015; Daumiller & Dresel, 2019; Molenaar et al., 2012; Munshi & Biswas, 2022; Schumacher & Ifenthaler, 2021; Siadaty et al., 2016a). Prior studies have identified challenges with learners' compliance in using scaffolds embedded in digital learning environments (e.g., standardized prompts, Moser et al., 2017; self-directed prompts, Pieger & Bannert, 2018); an underlying issue with scaffolds implemented in past research is that they were not sufficiently adaptive to learners' learning progress and personalized to individual learning needs. In order to effectively support SRL, scaffolds need to contain three crucial components which, together, fulfil the fundamental quality of adaptivity: 1) continuous diagnosis of learning progress, 2) calibration of support based on diagnosis, and 3) fading of support when no longer needed, i.e., when skills and knowledge have been internalized (Puntambekar & Hubscher, 2005). On top of the adaptive mechanism, support can be designed to be explicitly personalized to individual learner needs by tailoring the content of the support provided (L.-A. Lim et al., 2021; Pardo et al., 2019). In Pardo et al.'s (2019) study, they found higher levels of satisfaction with the personalized support given. The effectiveness of scaffolds has been found to differ based on how learners use them (e.g., Engelmann et al., 2021; Lallé et al., 2017; Moser et al., 2017). Furthermore, how learners experience (scaffold) tools influence how they use them (Gašević, Mirriahi, et al., 2017). Therefore, for scaffolds to be effective, they need to be inherently adaptive and their content personalized. In addition, scaffolds are effective when they support various SRL activities across different SRL phases (Zheng, 2016).

Although scaffolds which are adaptive are more beneficial for learning (Azevedo & Hadwin, 2005), there is still much room in the field for the development and testing of such scaffolds (Guo, 2022; Zheng, 2016). Prior research studies have focused on scaffolds which offered generalized support to learners, regardless of individual learning progress differences and needs (e.g., Bannert & Reimann, 2012; Daumiller & Dresel, 2019; Moser et al., 2017; Müller & Seufert, 2018; Schumacher & Ifenthaler, 2021; Wong et al., 2021). There have been attempts in previous studies to address limitations (e.g., learners' compliance) with static or fixed support interventions by providing user-driven support through self-directed prompts but these studies have also found that the intervention did not have the expected

positive effects on learning outcomes, possibly linked to learners not always using the scaffolds in the intended manner or not always having the necessary capacity to design effective prompts for themselves (Engelmann et al., 2021; Engelmann & Bannert, 2019; Pieger & Bannert, 2018). There have been a small handful of studies which embedded scaffolds of varying adaptivity in advanced and intelligent learning environments, which inclined towards the system-driven approach of externally supporting SRL (MetaTutor, Azevedo, Johnson, et al., 2010; AtgentSchool, Molenaar et al., 2012; Betty's Brain, Munshi & Biswas, 2022). For instance, the intelligent hypermedia learning environment, MetaTutor, fostered SRL in science learning through pedagogical agents which adapted support based on task progress (Azevedo, Johnson, et al., 2010). In a similar vein, Molenaar and colleagues (2012) implemented progress-based dynamic scaffolding to support socially regulated learning among dyads within a learning system, AtgentSchool, concentrating on learners' actions (or absence of actions, i.e., inactive) and attention for triggering scaffolds. In both systems, highly sophisticated designs of scaffold adaptivity were implemented, yet, not all three crucial components of (adaptive) scaffolds, such as the ongoing detection of learning behavior and fading, were incorporated. Nonetheless, in the recent update to the Betty's Brain system (Munshi & Biswas, 2022), an adaptive scaffolding framework was implemented within the open-ended learning system, which monitored ongoing learning behavior and detected key transition points for triggering contextualized scaffolds. Despite promising developments in (adaptive) scaffold interventions with ongoing diagnoses of learning and calibration of SRL support, there is still more work needed to include fading mechanisms and to integrate personalization of scaffolds to align with individual learner needs.

The field of artificial intelligence in education (AIED) has been shifting its focus on to metacognition in the last years (e.g., MetaTutor, Azevedo et al., 2019; Betty's Brain, Biswas et al., 2016; AutoTutor, Graesser et al., 2017; Help Seeking Tutor, Roll et al., 2006), especially with SRL research moving towards investigating the temporal and sequential qualities of learning behavior, and consequently the rise in use of various (novel) approaches to capture, analyze, and support SRL through interdisciplinary methods (e.g., by combining artificial intelligence and learning sciences) (Azevedo & Wiedbusch, in press). A major issue in implementing SRL support, especially in hybrid systems which combine human and artificial intelligence, however, is to strike a balance between supporting learners versus taking over regulation for learners (Molenaar, 2022). Circling back to how scaffolds adapt and personalize support to optimally support learning, a potential way to circumvent "over-external-regulation" is to support learners using predefined parameters in which support is

provided, i.e., by using a rule-based system, where the amount of external regulation is controlled but remains adaptive to learning progress and personalized to individual learners. To address both adaptivity and personalization in SRL support, however, it is crucial to tackle the central challenge of how to effectively capture SRL through the large amount of (trace) data a learner generates while learning, in real-time, analyze them instantaneously, and use the information to govern the support of learning in an adaptive manner fitting to the dynamic nature of SRL. The rule-based artificial intelligence (AI) approach introduced in the research presented in the current dissertation is an initial attempt to realize a threefold scaffolding design approach. The approach deals with adaptivity at the a) design-loop and b) step-loop of the adaptive learning technologies development cycle (Aleven et al., 2016), while c) personalizing support. Adaptivity at the design-loop refers to the design of learning technologies which are informed by past empirical findings and adaptivity at the step-loop refers to how the learning technology system adapts based on students' learning behavior during the task (Aleven et al., 2016).

5 The Present Research: Scaffolding Self-Regulated Learning with Advanced Learning Technologies

The previous sections introduced the theoretical foundation this dissertation was built upon, the link between SRL and learning outcomes, the importance of measuring SRL activities as they occur, analyzing the temporal and sequential characteristics of SRL beyond frequencies to facilitate optimal learning. The previous sections also presented arguments on supporting students' SRL through personalized scaffolds which adapt and cater to individual learning needs along with empirically testing effects of personalized scaffolds in order to continue to optimize such kinds of support. The central aim of the research presented in the dissertation is to progress SRL support with advanced learning technologies and to propose suggestions for theory development. Through the three key action steps introduced in section 1, real-time analytics-based personalized scaffolds which were grounded in theory and past empirical work were developed and their effects examined. The journal articles connected to this dissertation tackle the necessary action steps in more detail below.

5.1 Laying the groundwork for the development and improvement of Self-Regulated Learning scaffolds (Study 1)

In order to support SRL, there is a need to assess the actual macro- and micro-level SRL activities occurring within a specific learning task and context. Next, finding patterns and consistencies with past research as well as students' SRL deficits help to refine SRL support provided to students. The first study (Journal Article 1: "Temporal Assessment of Self-Regulated Learning by Mining Students' Think-Aloud Protocols") focused on the measurement and analyses of SRL in order to provide insights for developing and improving future SRL interventions, specifically scaffolds. The study addressed three research questions:

1. How do students (spontaneously) regulate their learning activities?
2. How do learning activities and their regulation correspond to learning performance?
3. How do the temporal structures of learning activities of successful and less successful students differ?

The study used a similar measurement and analysis approach as a previous study (Bannert et al., 2014) in order to determine if findings were still valid and consistent given a different learning task and context. For example, do micro-level SRL processes differ across learning tasks and contexts although general SRL models assume macro-level similarities

such as the three main phases of SRL? Think aloud protocols were recorded and then coded with an adapted coding scheme from prior research (Bannert, 2007; Sonnenberg & Bannert, 2015) and learning patterns of successful and less successful students were analyzed with a process discovery approach (i.e., Fuzzy Miner, Günther & Van Der Aalst, 2007). It was expected that a high number of learning activities would be detected, similar to past studies using the same coding scheme. Several past studies have also indicated a positive link between metacognitive activities and transfer performance (Bannert et al., 2014; Bannert & Mengelkamp, 2013; Müller & Seufert, 2018; Sonnenberg & Bannert, 2015) and this study sought to investigate if the same link was replicated. Finally, the study explored SRL patterns of successful and less successful students to establish if successful students had SRL patterns with the three main SRL phases as proposed by theory, similar to findings from prior research (Bannert et al., 2014), and where students (still) needed SRL support, i.e., SRL deficits.

5.2 Implement and test personalized scaffolds (Study 2)

The findings from the first study were used to support the design and development of personalized scaffolds examined in the second study (Journal Article 2: “Effects of Real-Time Analytics-Based Personalized Scaffolds on Students’ Self-Regulated Learning”) which built upon the first study and focused on the implementation and testing of (effects of) personalized scaffolds. The study addressed three research questions:

1. What are the effects of personalized scaffolding on students’ learning activities?
2. What are the effects of personalized scaffolding on students’ learning performance?
3. What are the effects of personalized scaffolding on the temporal structure of self-regulated learning activities?

The second study investigated personalized scaffolds and compared their effects to generalized scaffolds, and in addition a control condition (i.e., no scaffolds). Past studies which implemented scaffolds during learning found that higher frequencies of SRL activities, particularly metacognitive learning activities (Engelmann & Bannert, 2019; Sonnenberg & Bannert, 2015), promoted deeper processing (Bannert et al., 2009; van der Graaf et al., 2022). Additionally, personalized scaffolds were proposed to be more fitting for individual learning needs, and hence, expected to be more advantageous than generalized scaffolds which provided standard scaffolds for all students. Therefore, it was assumed that scaffolds, especially personalized scaffolds, would promote metacognitive activities as well as high cognitive activities (e.g., elaboration) in comparison to not having scaffolds. Previous scaffold studies have also found that scaffolds improved learning outcomes, especially

transfer performance (Bannert et al., 2015; Bannert & Mengelkamp, 2013; Guo, 2022; Lin & Lehman, 1999; Müller & Seufert, 2018; Zheng, 2016). Furthermore, the scaffolds implemented in this study were designed to support the learning task (i.e., writing an essay with the texts provided). Thus, it was posited that students who received scaffolds, especially personalized scaffolds, would perform better than students who learned with no scaffolds. The last research question was considered more exploratory in nature with regards to the analysis approach—process mining—which was complementary to statistical analyses for the investigation of the temporal and sequential nature of SRL. It was nonetheless generally expected that students engaged in considerable reading and writing activities due to the learning task, and in addition, monitoring having a more prominent role in the scaffolded groups because of the support received.

6 Methodology

Although the author of this dissertation played a leading role in the included studies, the studies were however embedded in a larger project, whereby there were other related studies, analyses, and publications using the same or similar materials and instruments. Hence, this section uses the pronoun, “we”, instead of “I”, to acknowledge the collaborative efforts of the other project members. There were more than five studies in various countries conducted within the project and the author of this dissertation led the studies presented in this dissertation as well as led the associated analyses (e.g., conceptualization of studies and research questions, analyses of research questions, development of materials, instruments, and scaffolds, etc.).

6.1 Project context

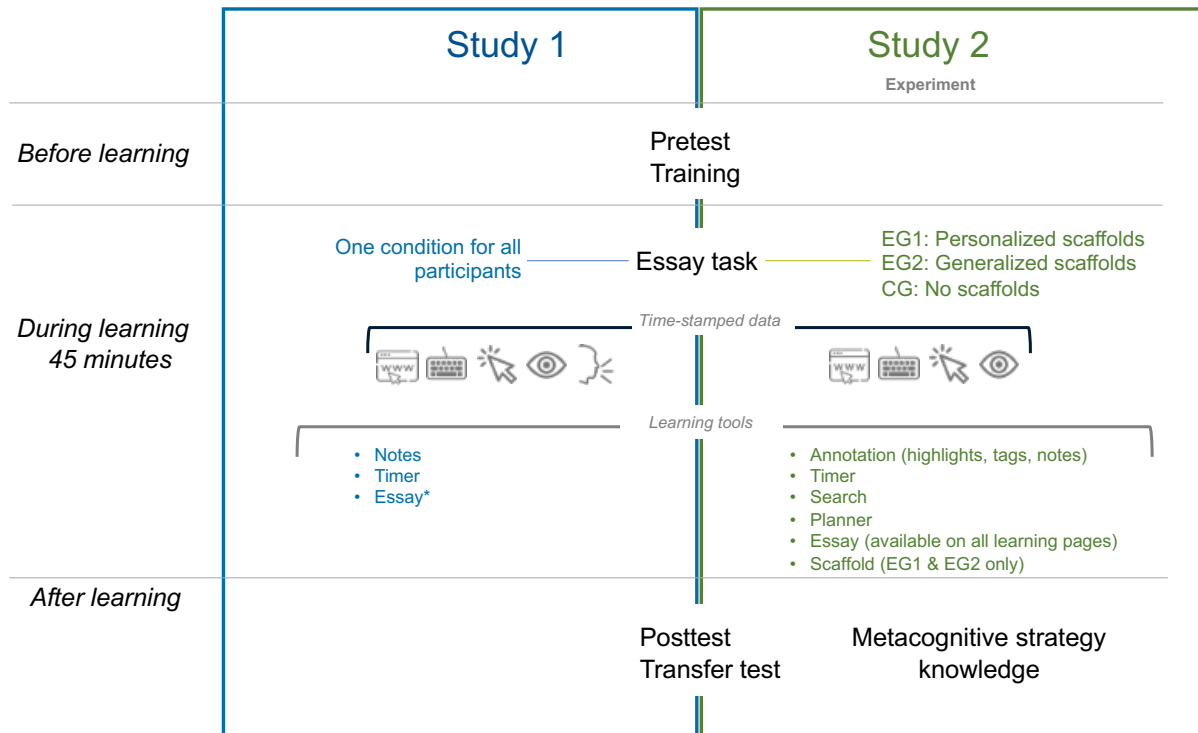
The research presented was embedded within a four-year international and interdisciplinary project, “Facilitating Self-Regulated Learning with Personalized Scaffolds on Students’ own Regulation Activities (FLoRA)” (www.floralearn.org). In Germany, the project was funded by the Deutsche Forschungsgemeinschaft (German Research Foundation) as part of the Open Research Area for the Social Sciences (DFG: BA 2044/10-1). The project aimed to integrate the fields of self-regulated learning and learning analytics in order to advance support provided to students through adaptive educational technologies. As part of the project, we developed an online learning environment incorporating learning (and instrumentation) tools. Additionally, a rule-based AI system was developed to measure and support individual students’ macro-and-micro-level SRL activities during learning within the learning environment. The funding agency had no influence on the study design, data collection, analyses, nor preparation and decision in the publication of the journal articles and dissertation. The following sub-sections describe the methodological approaches of both studies. Due to several similarities between both studies, the sub-sections describe the methods for both studies together. For clarity, whenever there are differences between the studies, the study which the specific details were described is explicitly stated.

6.2 Research design

Study 1 had a pre-posttest design and study 2 had an experimental pre-posttest between-subject design. Figure 2 illustrates the similarities and differences between the two studies. The learning environment used was greatly enhanced in the second study with the addition of more learning tools and upgrades to existing tools. All learning tools embedded in the learning environment of the second study were accessible on all learning pages.

Figure 2

Research design of the empirical studies in the dissertation



Note. *not tool *per se* but included as a separate page.

6.3 Participants and procedure

The samples of both studies presented consisted of university students enrolled in German universities. Participants were recruited in a similar manner through open recruitment drives via e.g., flyers and the participant recruitment portal, with identical participation criteria: 1) currently matriculated university students (excluding PhD students), 2) with German as first language. Participation was voluntary and participants were reimbursed monetarily. The participants in both studies studied a diverse range of degree majors (more than 25). The studies complied to the American Psychological Association Ethics Code (APA, 2016) and all participants gave active consent prior to their participation. Both studies were conducted in one-to-one sessions in the laboratory with an experimenter present at all times. The study sessions consisted of four parts. The first part was the pretest phase where participants completed the demographic questionnaire and the pretest instrument. The second part was the introduction and training phase where participants were introduced to the learning environment and tools. The third part was the learning phase where participants learned using the texts provided in the learning environment and wrote an essay. The final part was the posttest phase where students completed the posttest and transfer

instruments. The following paragraphs detail the sample and procedural differences between the two studies. Comprehensive descriptions of the samples and procedures for both studies can be found in the respective publications (see appendices A and B).

6.3.1 Study 1

The first study was conducted between June and July 2019. Valid and usable data were available for 29 out of 36 participants. Each participant received 15 euros for their participation. In the training phase in part two of the study session, participants were additionally guided through a 10- to 15-minute think aloud training. The experimenter first demonstrated how to think aloud while navigating through a sample page of the learning environment, which included the learning tools. The demonstration was scripted so every participant received the same demonstration. The participants were then asked to practise thinking aloud while performing short exercises which involved navigating through the learning environment and using each of the learning tools. The experimenter provided feedback regarding the participants' think aloud verbalizations at the end of the practice. For example, the experimenter informed participants that they needed to be louder or that they needed to continue verbalizing even when reading the text. The participants were then instructed to think aloud as they were reading and learning during the 45-minute learning phase—part three of the study session. The experimenter prompted the participants to continue thinking aloud whenever they fell silent for more than five seconds and/or spoke too quietly.

6.3.2 Study 2

The second study took place between November 2020 and December 2021 with usable and error-free data for 98 out of 104 participants. Each participant received 20 euros for their participation. Due to local COVID-19 measures, there were multiple breaks within the one-year data collection period but the participant recruitment was performed in the same way each time data collection was able to be resumed. In the posttest phase of the study session, participants additionally completed a metacognitive strategy knowledge questionnaire (MESH; Bannert, Pieger, & Sonnenberg, 2015) which collected information about the participants' prior metacognitive strategy knowledge. The MESH was administered at the end of the session since the study did not include intervention targeted at altering metacognitive strategy knowledge. Based on previous lab and pilot studies, past participants also provided feedback that having the questionnaire at the end of the session was more manageable than at the pretest phase.

6.4 Learning materials and measures

6.4.1 Learning materials

The participants in both studies 1 and 2 learned using learning materials comprising of texts and figures from three topics: artificial intelligence (AI), differentiation in the classroom, and scaffolding. The expository texts were extracted from textbooks and scientific articles, characteristic of the texts students at the tertiary level education often encounter. The texts were translated to German for the purpose of the studies. A text readability analysis (Michalke, 2012) indicated the texts to be sufficiently challenging for students at the university level (see Table 1).

Table 1

Text readability analysis of the learning materials

| Topic | Text length | Flesch-Kincaid grade-level score ¹ | Flesch Reading Ease ² |
|----------------------------------|-------------|---|----------------------------------|
| Artificial Intelligence | 2126 words | 15.56 | 41.42 |
| Differentiation in the classroom | 1309 words | 21.33 | 22.41 |
| Scaffolding | 1802 words | 19.84 | 28.39 |

Note. ¹ This more common Flesch-Kincaid Grade Level formula converts the Reading Ease Score to a U.S. grade-school level. The higher the number, the harder it is to read the text. The grade levels range from 0 to 12.

² The output of the Flesch Reading Ease formula is a number from 0 to 100, with a higher score indicating easier reading. The average document has a Flesch Reading Ease score between 60 and 70.

6.4.2 Instruments and measures

The learning performance measures in both studies were developed based on the Bloom's taxonomy of cognitive learning objectives (Bloom et al., 1956). Domain knowledge, assessed through multiple-choice items for both pre- and posttests, focused on comprehension of the specific concepts introduced in the texts. The internal consistency of the domain knowledge test was $\omega = 0.62$ to 0.75 ($\alpha = 0.61$ to 0.68). Transfer knowledge was assessed through a multiple-choice test and required students to apply their knowledge in a different situation. In the first study, the transfer test consisted of 10 items where students applied their knowledge of artificial intelligence in a medical setting. Internal consistency of the instrument was found to be $\omega = 0.44$ ($\alpha = 0.35$). In the second study, we extended the transfer test by adding 16 additional items to assess transfer of knowledge of the two other learning

topics to different situations—differentiation in the workplace and scaffolding in sports. The decision to do so was based on two factors. First, we wanted to eliminate the possibility that students who had a strong focus on the AI text had an advantage in the transfer test. Second, having all three text topics provided the possibility for more detailed comparison analyses with the essays which required students to integrate all topics. Internal consistency of the instrument was found to be $\omega = 0.53$ ($\alpha = 0.52$) after removing three items which had negative correlations to the rest of the items.

To assess the application and integration of knowledge from the three learning topics, students in both studies were tasked to write a short essay about how the future of learning in schools would look like, supporting their ideas with the concepts introduced in the texts. Trained coders graded the essay content manually using a coding scheme (see Appendix C). As part of the final essay score, an originality score was calculated using an anti-plagiarism software (WCOPYFind, Bloomfield, 2016) to detect the amount of essay text copied from the learning texts. Metacognitive strategy knowledge was assessed with the Metacognitive Strategy Inventory for Hypermedia Learning (MESH) (Bannert, Pieger, & Sonnenberg, 2015) questionnaire and consisted of seven learning scenarios where students had to rate the suitability of up to six learning strategies in each learning scenario.

6.5 Measuring and supporting learning activities

6.5.1 Study 1: Think aloud coding

In the first study, we measured SRL activities via think aloud protocols. This section details the procedure on how the think aloud preparation and coding were performed. A list of the think aloud codes can be found in the journal paper (Appendix A). We recorded students' concurrent verbalizations during the 45-minute learning phase, including both audio and screen recordings. We adapted the think aloud coding schemes from prior research (Bannert, 2007; Sonnenberg & Bannert, 2015): First, we used a speech-to-text software (i.e., *Amazon Transcribe*, n.d.) to automatically generate a transcription of the verbalizations of one recording. Then, a native speaker checked and edited the transcript for language-related issues (e.g., replace wrong words, insert missing words etc.). The learning scientists in the project team, including the author of this dissertation, checked through the categories of the coding scheme and adapted and refined the (sub-)categories using both the transcription and also the audio and screen recording. Representative examples of each coding category were then extracted and inserted as additional information into the coding scheme for training

purposes. Subsequent examples were included during the coding process, whenever they were relevant and highly representative of the respective codes.

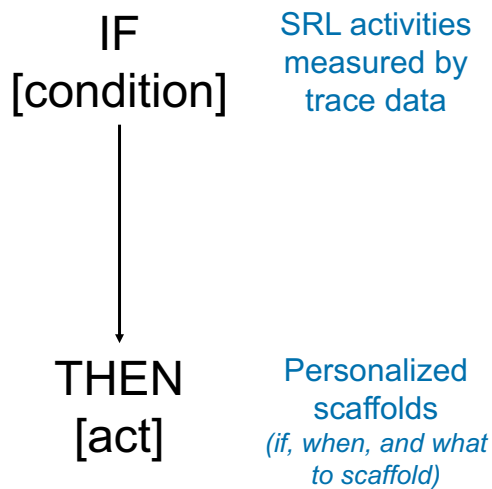
There were two stages in the think aloud coding process. In the first stage—the training stage, coders were trained by the author of this dissertation on both the think aloud coding categories and the coding procedure (e.g., how to insert codes into the time-stamped segment accordingly). Each coder was trained for about one week, including discussions with the coding team (i.e., the author of this dissertation and the other coder). In the second stage—the coding stage, the trained coders independently coded the same subset of the think aloud protocols and interrater reliability was assessed to be excellent ($\kappa = 0.95$) before independent coding was performed. To prepare for the coding, we first performed automatic segmentation using an audio software (*Audacity*, n.d.) to detect parts of the recording with sound (i.e., not silent). Then, using an audio and video annotation software (ELAN, Sloetjes & Wittenburg, 2008), segments were adjusted (e.g., added, removed, merged) by the human coders, when highly necessary. Each segment was determined to be the smallest unit of meaning based on Chi's (1997) procedure. Segments with irrelevant sounds and no meaning (e.g., typing, sneezing, etc.) were removed. The same coder then assigned a code to each segment.

6.5.2 Study 2: The rule-based AI system for measuring and supporting Self-Regulated Learning

As part of the project, we developed a rule-based AI system for measuring and supporting SRL. Such rule-based AI systems are dependent on the rules determined by domain experts. In the case of this project, the learning scientists in the research group acted as the domain experts. These rules have a general structure of a conditional statement: IF [condition] THEN [act] (Flasiński, 2016). The IF [condition] was modeled from SRL activities coded from trace data (see Figure 3), i.e., also referred to as the input to the personalized scaffolding model (see also Figure 5). These conditions indicated if and when support was needed and which SRL activities to support. The THEN [act] was implemented as personalized scaffolds.

Figure 3

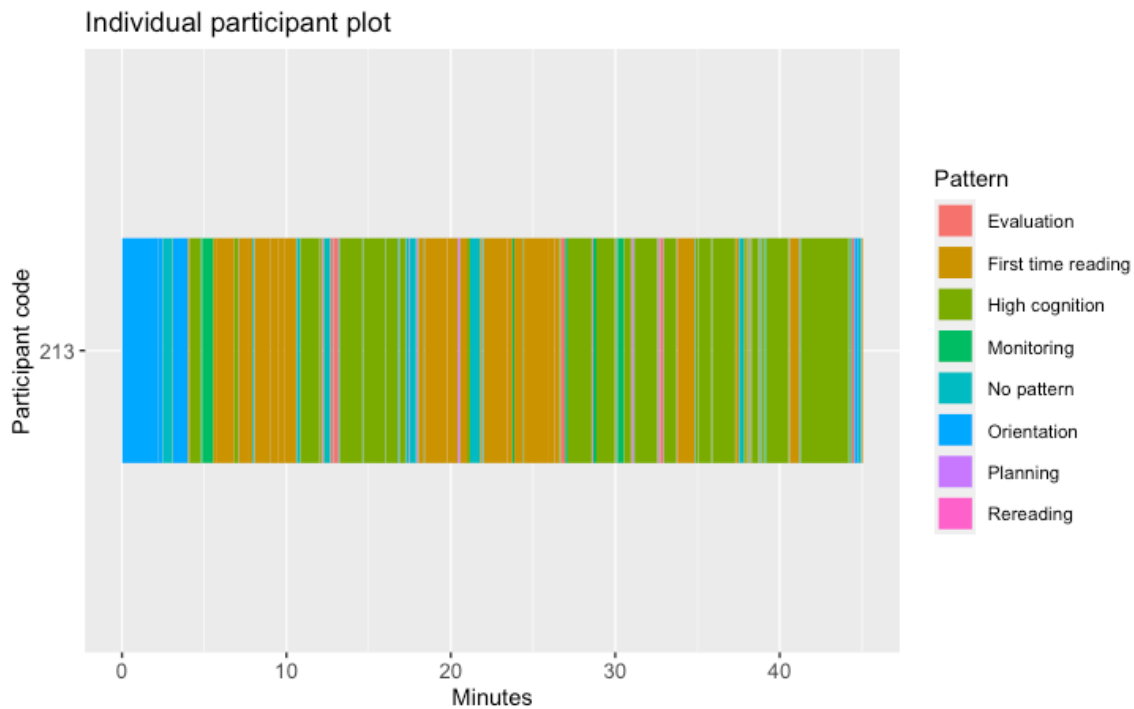
The application of the rule-based AI system used in the study



In this study, SRL activities were measured through trace data. This paragraph summarizes the trace data coding protocol. Further information about the trace data codes can be found in the journal paper (Appendix B). We recorded time-stamped students' interactions with the learning environment (i.e., trace data such as keyboard strokes, navigational logs, and mouse clicks) during the 45-minute learning phase in the second study. Based on the theoretical framework of the think aloud coding scheme, we developed a coding protocol of SRL activities using trace data—also known as the analytics-based SRL measurement protocol. The raw trace data were first parsed to meaningful learning actions (e.g., relevant reading); sequences of learning actions (e.g., rubric to navigation to relevant reading) were then mapped to SRL activities (e.g., orientation). Figure 4 visualizes the SRL activities coded from trace data of one participant in the learning session of 45 minutes.

Figure 4

A visualized example of the activities coded for one participant



Using the SRL activities measured, the personalized scaffolding model executed analytics-based decisions such as whether students have completed specific SRL activities and what further SRL activities do they need support in. Figure 5 summarizes the process. Students received up to five scaffolds during learning (see Figure 6).

Figure 5

The personalized scaffolding model

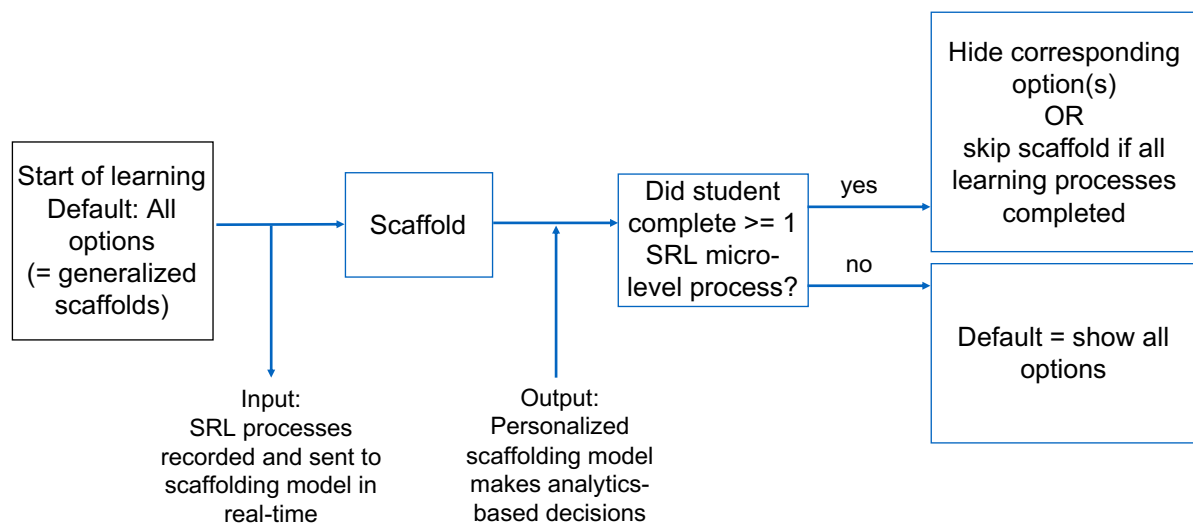
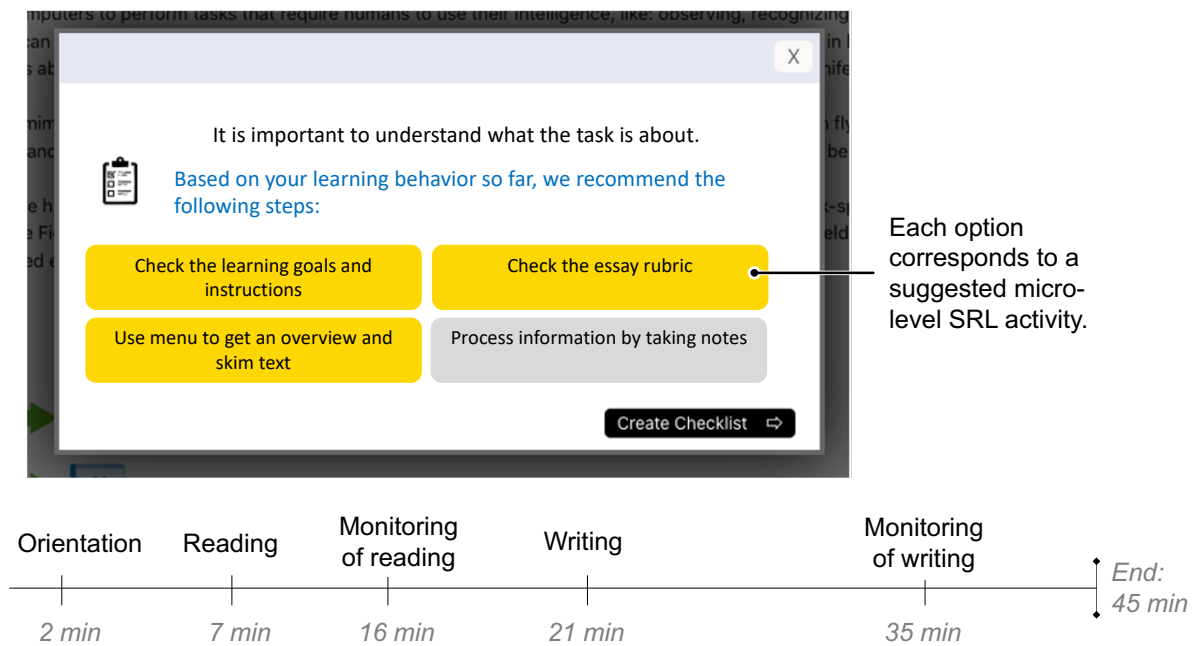


Figure 6

An example of a personalized scaffold and the scaffold trigger intervals



6.6 Analyses

To investigate the research questions, descriptive statistical methods were first used in both studies to analyze the data, e.g., investigate the frequency of SRL activities and also performance measures. Then, inferential statistics were used to examine mean differences. Finally, process analysis was conducted to examine SRL patterns. In the first study, a paired samples *t*-test was used to determine learning differences between pre- and post-test scores. Non-parametric correlational analyses (Spearman's rank correlation coefficient) were performed to examine the relationship between frequency of various SRL activities and performance scores. Successful and less successful students were operationalized based on a median split approach. Using a process mining framework (ProM; Verbeek et al., 2011), a process discovery algorithm, Fuzzy Miner (Günther & Van Der Aalst, 2007), was then applied to the time-stamped think aloud event logs of the two groups of students. In the second study, analyses of variance (ANOVAs) were conducted to test for group differences in metacognitive activities and performance variables. Multivariate analysis of variance (MANOVA) and follow-up ANOVAs with Bonferroni correction were used to examine differences in individual SRL activities. Stochastic process mining using pMiner (Gatta et al.,

2017) was used to visualize trace data event logs as well as produce comparison diagrams between groups.

7 Summary of Publications

7.1 Study 1: “Temporal Assessment of Self-Regulated Learning by Mining Students’ Think-Aloud Protocols”

(see L. Lim et al., 2021, Appendix A)

It is well documented in past theoretical and empirical work that self-regulated learning (SRL) has been linked to desirable learning outcomes, particularly in deep knowledge tasks (Panadero, 2017; Schunk & Greene, 2017). During SRL, learners actively decide on the metacognitive and cognitive strategies they execute to monitor and control their learning in pursuit of their goals (Pintrich, 2000; Winne & Hadwin, 1998). SRL models commonly assume three main cyclical phases (e.g., COPES model, Winne & Hadwin, 1998; SRL from a socio-cognitive perspective, Zimmerman, 2000), though regulatory activities do not always take place in a rigid sequence (Azevedo, 2009). Previous empirical studies have particularly found that metacognitive activities, such as monitoring, were linked deep learning activities, and likely, better performance in deep knowledge tasks like transfer tests (Bannert & Mengelkamp, 2013; Greene & Azevedo, 2009; Sonnenberg & Bannert, 2015; van der Graaf et al., 2022). Nevertheless, learners sometimes experience difficulties regulating in online settings as they often have to independently navigate the learning environment where tasks, tools, and support are embedded while making decisions on how to learn and complete the tasks, thus needing further support (e.g., Azevedo, Johnson, et al., 2010; Molenaar et al., 2011). Additionally, SRL is made up of complex and dynamic activities which are constantly adapted as learners regulate their learning (Winne, 2010). Capturing SRL activities as they occur offers the opportunity for researchers to model and investigate the dynamic nature of SRL processing (Molenaar & Järvelä, 2014). Online methods such as (concurrent) think aloud align more accurately with actual SRL behavior and are strong predictors of achievement (Rovers et al., 2019; Veenman, 2013). Therefore, the first study investigated students’ strengths and gaps in SRL in an online learning setting by modeling and comparing successful and less successful students’ SRL activities recorded using think aloud protocols. The aim of the study was to extend previous research—whether past research findings were replicated and consistent in a different learning task and context—as groundwork for future SRL support.

It can be a challenge to compare findings across studies investigating SRL due to different approaches used as well as types of data and the respective data granularity. Hence, in order to determine consistency of findings, a similar process analysis approach from a past

study (i.e., Bannert et al., 2014) was used. In a pre-post-test design laboratory study with a final sample of 29 university students with diverse academic backgrounds, concurrent think aloud protocols during a learning task and test responses were collected. The findings showed that using an adapted coding scheme from past research (Bannert, 2007; Bannert et al., 2014) permitted the observation of fine-grained SRL activities in all SRL phases. The positive correlation between metacognitive activities and transfer performance was similarly found. By means of modelling successful and less successful students' SRL activities, patterns comparable to past findings were found, especially in terms of successful students' learning, despite a different learning task and context. The results demonstrated coherence to previous findings from Bannert et al. (2014) in terms of frequencies of SRL activities of successful and less successful students; successful students performed more metacognitive and deep cognitive activities. The process model of the successful students also exhibited more similarities to SRL models as proposed from theory. In general, students, regardless of success level, continued to perform little planning and evaluation activities, as found in previous research. Several unique findings were also found. First, (selective) rereading seemed to have played a different and important role in successful learning. Second, unlike in past research, less successful students also engaged in frequent deep learning activities such as elaboration and organization but these activities seemed to occur in an isolated manner from the rest of the activities such as monitoring. Third, although the process model of the successful students illustrated multiple interconnected activities, the link between elaboration and evaluation was weaker than links between other activities and also in comparison with previous findings.

In summary, the findings from the study showed various consistent findings with past research, illustrating the stable benefits of specific SRL activities across learning tasks and contexts, like monitoring. The study also replicated the link between metacognitive activities and transfer performance. Additionally, the study further validated the think aloud approach to measuring SRL which showed that think aloud protocols can be used as a basis for validating other measurement protocols, such as analytics-based SRL measurement protocols using trace data. Finally, insights from the study, such as strategic sequences of activities and when to employ them, can be used for future SRL intervention development.

7.2 Study 2: “Effects of Real-Time Analytics-Based Personalized Scaffolds on Students’ Self-Regulated Learning”

(see Lim et al., 2023, Appendix B)

Based on findings from the first study, successful students not only exhibit strategic sequences of SRL activities but also executed them at specific times. Furthermore, results from the first study indicated the importance of metacognitive activities and their link to transfer achievement, as prior studies have consistently shown (e.g., Bannert et al., 2014). Prior research has also found that enhanced learning outcomes can be achieved through scaffolding of SRL activities since SRL has been well-linked to learning performance (Bannert et al., 2015; Dent & Koenka, 2016; Guo, 2022; Schunk & Greene, 2017; Zheng, 2016). This is particularly relevant as students’ spontaneous regulation of learning and successful SRL in online learning settings remain a challenge to be tackled (Azevedo & Feyzi-Behnagh, 2011; Flavell et al., 1966; Veenman et al., 2005). However, past scaffold interventions did not always fully account for the dynamics of SRL processes, and hence, had varied effects on learning (e.g., standardized prompts, Moser et al., 2017; self-directed prompts, Pieger & Bannert, 2018). In order to support students’ learning in an optimal way, scaffolds need to continuously adapt and calibrate to students’ ongoing learning progress (Puntambekar & Hubscher, 2005) and cater to individual learning needs (Pardo et al., 2019). Therefore, scaffolds need to be both inherently adaptive and also personalized. Although research in the past years have developed adaptive scaffolding systems (e.g., Metatutor, Azevedo, Johnson, et al., 2010; Atgentive, Molenaar et al., 2012; Betty’s Brain, Munshi & Biswas, 2022) and also personalized feedback systems (L.-A. Lim et al., 2021; Pardo et al., 2019), these systems are still uncommon and do not integrate both aspects. To address this gap, we developed a personalized scaffolding model driven by a rule-based AI system utilizing students’ ongoing learning activities measured by trace data (i.e., analytics-based). The study aimed to investigate the effects of personalized scaffolds on learning activities, learning outcomes, and the temporal structure of SRL activities, as the initial steps to further advance scaffold interventions with suitable AI technologies and methods.

Using a pre-post between-subject experiment, effects of personalized scaffolds (EG1, $n = 35$) were compared with generalized scaffolds (EG2, $n = 30$) and a control condition with no scaffolds (CG, $n = 29$). Students in the generalized scaffold condition received scaffolds which did not take into account ongoing learning; all students received the same number of scaffolds and the same scaffold support content. Descriptive differences in SRL activities

between all groups were detected. Hypothesis tests revealed that personalized scaffolds significantly induced monitoring and high cognitive learning activities when compared with the control group. However, no effects of personalized scaffolds were found on all learning outcomes, against expectations. The First order Markov models (FOMMS) of SRL activities of each group as well as comparison FOMMs between the groups indicated pronounced similarity in the temporal structure of learning activities, potentially explaining why no learning outcome differences were detected between the different conditions.

In conclusion, the findings of the second study demonstrated how analytics-based personalized scaffolds based on real-time measurement and support of SRL activities is realized using a rule-based AI system. There were multiple plausible explanations for the findings that should also be researched further, such as whether a structured learning environment with embedded learning tools could already support SRL activities or if proficiency in scaffold use and tools leads to effects on learning outcomes. Nonetheless, further research opportunities include testing personalized scaffolds in different tasks and contexts and capitalizing on machine learning methods which does not restrict personalized scaffolds to pre-determined rules.

8 General Discussion

The general aim of this dissertation was to bring about greater understanding of the improvement and effects of advanced learning technologies in supporting SRL and providing suggestions for theory development. The empirical studies included in the research presented addressed why and where students need SRL support (first study), which SRL aspects to support (first and second study), how to support students' SRL and what the effects of personalized scaffolds are (second study). This section summarizes the main findings and limitations, and discusses the implications for research and practice as well as future research directions.

8.1 Self-Regulated Learning and Self-Regulated Learning Processes: “Why and where do students (still) need Self-Regulated Learning support?”

The first study contributes to the research need of extending prior research by investigating consistency and generalizability of findings in a different learning context and task. Building on this, the first study also contributes to the research need of developing and optimizing SRL support by laying the groundwork for differentiated SRL support that meets a diverse range of needs, particularly in digital and online settings. The foremost observations from the first study established that the think aloud coding scheme adapted from prior research provided observations of students' SRL at a fine granularity even when a different learning task and context was used, which formed an adequate basis for the comparison of findings. The granularity differences—at times due to the modality differences in observations as well—between numerous studies which investigated SRL in digital and online settings (e.g., Jansen et al., 2020; Taub et al., 2022) make it difficult for recommendations to be incorporated directly into improving SRL support, especially in new learning tasks and contexts. For example, several studies have investigated SRL on a course-level (e.g., Kizilcec et al., 2017; Wong et al., 2019), subject-specific level (e.g., Huang & Lajoie, 2021; Lin & Lehman, 1999), context-specific level (e.g., Sha et al., 2012), or age-group-specific level (e.g., Dignath & Büttner, 2008; Heirweg et al., 2019). Therefore, findings from the first study were reflected particularly closely with a previous study (i.e., Bannert et al., 2014) which used a similar approach (e.g., SRL coding scheme, think aloud protocols).

Research in the field of SRL have well documented evidence of the link between SRL and improved learning (Dent & Koenka, 2016; Schunk & Greene, 2017; Zheng, 2016),

especially transfer performance (Bannert et al., 2014; Bannert & Mengelkamp, 2013; Müller & Seufert, 2018), but also highlighted students' shortfalls in spontaneously regulating their learning (Azevedo & Feyzi-Behnagh, 2011; Flavell et al., 1966). Findings from the first study of this dissertation echoed comparable results; as with past studies, metacognitive activities were found to be positively correlated with transfer performance. Furthermore, successful students engaged in significantly more metacognitive activities, particularly monitoring, than less successful students, as Bannert and colleagues (2014) have likewise found. Successful students also engaged in more deep cognitive activities. Increased metacognitive activities often go hand-in-hand with a deep approach to learning, a finding which has been consistently found in past studies to be linked with improved transfer performance (Bannert et al., 2014; van der Graaf et al., 2022). A deep approach to learning can be described as the deployment of a combination of metacognitive activities and deeper cognitive activities. In Bannert and colleagues' (2014) study, they found that students who were the most successful in a transfer task monitored diverse learning activities and elaborated on information more deeply in comparison to less successful students who focused more on superficial processing, such as repeating, than deeper processing. Van der Graaf et al. (2022) correspondingly found that metacognitive activities were positively related to performance on deep knowledge tasks (i.e., better transfer and essay scores). According to them, there could also be a so-called "trade-off" between the SRL activities students engaged in and the learning outcomes they promoted, e.g., surface knowledge tasks like domain knowledge tests versus deep knowledge tasks like transfer tests. Hence, a deep approach to learning could also be assumed to be ideal for fostering deep knowledge and facilitating the transfer of knowledge to new situations. How metacognitive activities, especially monitoring, foster the acquisition of deep knowledge through deeper cognitive processing, can be explained with the support of the SOI (Selection-Organization-Integration) model (Mayer, 1996). The SOI model proposes that students first strategically select relevant and important information for learning. This is in line with SRL models where students first analyze the task by engaging in orientation, planning, and goal setting activities (e.g., what is to be learned, what are the goals for learning), thereafter they continuously monitor their learning (e.g., what is relevant for the task and to achieve their goals). The second strategy proposed by the SOI model is organization, where students meaningfully organize selected relevant information. The last strategy proposed by the SOI model is integration, where information in the short-term memory is integrated with knowledge from the long-term memory. By means of metacognitive activities, such as metacognitively monitoring learning, and deep cognitive

activities, e.g., organization—organizing information into a clear structure, and elaboration—connecting new information with prior knowledge through explanation, students are then able to effectively transfer their (deep) knowledge, as evidenced by more superior transfer performance found in the presented study as well as prior research.

The findings indicated that successful students engaged not only in more activities that were conducive to productive SRL but also at the same time more strategically. Moreover, the first study also revealed that successful students could still need support in typically rare-occurring activities, such as evaluation. Therefore, to address the question, “why and where students (still) need SRL support”, the research from this dissertation illustrated that similar to previous studies, students encounter difficulties with spontaneous regulation of learning and require support. Furthermore, the findings provided more certainty, through replication of past findings, which findings were generalizable, such as how successful learning looks like, in terms of consistency with theoretical assumptions as well, how to support less-than-optimal SRL and additionally, how to differentiate support to further improve successful students’ regulation of learning.

8.2 Development and testing of Self-Regulated Learning support: “How to support students’ Self-Regulated Learning and what the effects of personalized scaffolds?”

The second study contributes with insights into the development of advanced learning technologies by testing the effects of personalized scaffolds. The second study built upon the findings of the first study, which provided the basis for defining parameters in the rule-based AI system that facilitated the real-time SRL measurement and support. Through an experimental design which compared the effects of personalized scaffolds with generalized and no scaffolds, findings from the second study demonstrated that SRL deficiencies (i.e., gaps in metacognitive activities) found in the first study can be more effectively supported with personalized scaffolds. Personalized scaffolds increased the frequency of metacognitive activities, especially monitoring, in comparison to generalized scaffolds. Students supported with personalized scaffolds also engaged in more high cognitive activities when compared to not having scaffolds. These findings also reflected that personalized scaffolds supported a deeper approach to learning. However, unexpectedly, learning performance effects were found to be absent, with highly similar learning scores found across treatment and control groups. Yet, this finding is not entirely unique. Past experimental studies (Engelmann & Bannert, 2019; Pieger & Bannert, 2018) have also found that differences in learning behavior

(e.g., differences in frequencies of metacognitive activities) occurred with effects missing in learning outcomes and deeper analyses (e.g., temporal analyses) needed to explain the inconclusive results.

Several scaffolding studies have reported students' poor compliance with the support provided, leading to missing scaffold effects on learning outcomes (Bannert, 2007; Bannert et al., 2015; Bannert & Mengelkamp, 2013; Engelmann et al., 2021; Moser et al., 2017). The manner in which students process the support (or materials) provided and the consequent actions they take is critical to the effect on learning. According to Rothkopf's (1970) concept of mathemagenic activities—activities that “give birth to learning” (p. 325)—students engage in different activities that could promote learning (i.e., mathemagenic positive), have no effect on learning (i.e., mathemagenic neutral), or even detrimental to learning (i.e., mathemagenic negative). In connection with the present research, a possible explanation for the missing learning outcome effects is that the suggested activities provided by the (personalized) scaffolds interfered with students' own, sometimes sub-optimal, strategies, leading to students proceeding with their own strategies than try to implement the new ones. However, when students are given more opportunities to learn to process the support provided, effects could be seen later. As proposed by the overlapping waves theory (Siegler, 1998), learners do not always engage in the same learning approaches or strategies; rather, they use multiple strategies which co-exist and sometimes compete, thus, some strategies are at times more dominant. Older and less effective strategies may prevail for prolonged periods before newer and better strategies gradually replace them. Hence, it is critical to continue to test personalized scaffolds in subsequent studies to investigate the stability of findings.

Since students do not typically learn with personalized scaffolds and also the learning tools embedded in the learning environment, they may be less proficient in using them, hence needing substantial effort, and thereby potentially experienced additional cognitive load. According to Seufert (2018), the level of a learner's regulation of learning is influenced by the task difficulty, individual's resources, and cognitive load. As one's resources decreases, coupled with high task difficulty, there is high load perceived and regulation declines. Gašević, Mirriahi, and colleagues (2017) found that development of proficiency in using learning tools (e.g., scaffolds) is requisite for students to recognize their value. Potential cognitive overload can be decreased by having adequate time and practice as less conscious effort is needed (Sweller et al., 1998). Hence, when students have a good grasp of the use of the tools provided, they have more resources available to better regulate their learning. Furthermore, this study was a first attempt at testing personalized scaffolds and more

extensive refinement and testing are required. Thus, to address the question, “how to support students’ SRL and what the effects of personalized scaffolds”, the research from this dissertation developed and implemented personalized scaffolds in an experimental study but found that while personalized scaffolds influenced learning activities more effectively, learning outcome effects were found to be absent, necessitating additional fine-tuning and adjustment to the current developed scaffolds along with further investigation. Implications for future (personalized) scaffold studies are elaborated in section 8.4.3. The next subsection goes into more detail about the insights gained from temporal analyses of SRL.

8.3 Temporal analyses of Self-Regulated Learning: Beyond frequency measures

Both studies presented in this dissertation contribute by investigating how SRL dynamically unfolds over time through process mining approaches. Process models enable the observation of the temporal structure of learning activities beyond singular activities and frequency analysis, delivering a more comprehensive understanding into how and when SRL activities occurred, and how they are connected to each other. Specifically, in this dissertation, SRL processes of successful and less successful students were modelled in the first study, and in the second study, the process model of students who received personalized scaffolds was compared with students who received either generalized or no scaffolds. Findings from the first study revealed that the process model of successful students corresponded more with theoretical SRL models, with the main SRL phases identifiable. In addition, the process model of successful students showed better integration of learning activities, in comparison to less successful students, who engaged in activities—also typically beneficial activities such as deep cognitive activities—in a disjointed manner. The temporal arrangements of learning activities of successful and less successful students additionally revealed differences in how specific strategies were used in each group and offered possible explanations for differences (or no differences) found in frequencies. For example, successful students engaged in rereading activities significantly more than less successful students. However, rereading is commonly considered a more superficial cognitive activity and does not benefit learning in the same way as deep cognitive activities (Dunlosky, 2013; Weinstein & Mayer, 1983). Yet, the process models illustrated that successful students used rereading differently than less successful students; they reread the text selectively, while taking notes and monitoring their learning. This finding suggests that successful students included rereading activities in a more strategic manner, which supports what previous research (i.e.,

Matcha et al., 2019) has also found. In a similar vein, Rakovic and colleagues (2022) found that students who performed well in a demanding multi-source essay task continuously monitored their work in the learning session; they tend to consider task goals and metacognitively monitor their learning and essay in order to take remediation actions (e.g., revising the essay). In the case of the first study, the selective rereading activities could be assumed to be remediation actions based on monitoring activities.

Temporal analyses findings from the second study provided further explanation as to why learning outcomes did not differ between treatment and control groups and how differences in frequencies of learning activities influenced learning in each group. Process models of all groups showed comparable patterns of learning activities and provided evidence that students who received no scaffolds also engaged in learning activities similarly as students who received support. Interestingly, with or without scaffolds, students were able to integrate monitoring activities well in their learning, a finding that deviates from past research (e.g., Engelmann & Bannert, 2019). This finding also contradicts findings from the first study (i.e., L. Lim et al., 2021) which demonstrated that less successful students monitored limited activities. Nevertheless, a consideration is that the learning environment and tools were comparatively more sophisticated in the second study (refer to Figure 2 in Section 6.2). For example, the learning tools in the second study were embedded as plugins that were easily accessible on all learning pages in comparison to the first study where the essay field was on a separate page which required frequent switching between reading texts and essay writing. According to Bannert (2009), control group students could also regulate their learning spontaneously. Additionally, in the case of this study, the learning environment was more structured than a completely open-ended environment and included specific learning tools that could have also supported as well as cued learning. Findings also showed that personalized scaffolds generally reinforced SRL activities, such as monitoring and high cognition, which students were already performing. Despite having personalized scaffold support, students continued to engage in little evaluation and planning activities, suggesting a need for more focused support on these activities. However, aggregating patterns of learning by treatment groups could be informative to a lesser extent to understand within-learner processes which are concealed (Winne, 2017b). As reflected by the first study, operationalizing representative groups of learners, i.e., more or less successful learners, provided more clarity in terms of understanding the SRL patterns which occurred. Following up from this dissertation, a next potential step ahead is to combine the approaches from both studies 1 and 2 in a future study to investigate how successful versus less successful students

within each scaffold group regulated their learning and used the support provided in order to further uncover the effects of personalized scaffolds with the goal of improving the development of SRL support. Both studies included in this dissertation delivered different insights from temporal analyses and offered more explanatory power into the findings. In the first study, initial differences between successful and less successful became more pronounced when examining how SRL activities unfolded. In the second study, process models offered more explanation as to why no learning outcome differences were found between groups by indicating similarities in the temporal structure of learning activities.

8.4 Implications: “What do the findings imply for research and practice and how to go ahead?”

The research presented in this dissertation has implications from theoretical (Section 8.4.1), methodological (Section 8.4.2), and practical (Section 8.4.3) perspectives.

8.4.1 Theoretical implications

From a theoretical perspective, the research presented in this dissertation calls for more attention to be placed on developing SRL models which are more sufficiently fine-grained. As Molenaar and Chiu (2014) have brought up in the context of collaborative learning, current theoretical models lack specificity, especially in terms of micro-level activities and how they relate to each other. Investigating SRL at a micro-level, as in the studies presented, highlights the role of context in SRL. Study 1 largely reflected the generalizability of specific findings, yet there were findings which were context-specific, such as how particular micro-level activities were included in students’ repertoire of learning activities and how they were beneficial for the learning task, when used appropriately. Study 2 reflected how personalized scaffolds are implemented at a fine-grained level, targeting micro-level activities which are contextualized to the learning task, such as orientation through reviewing the essay rubric or checking the task instructions. During the course of the present research, there was the challenge regarding granularity discrepancy in terms of making fine-grained decisions while referencing to more “general” theoretical models. Nevertheless, the present research provides more clarity by adding to the body of research which examines SRL using an event-based perspective, uncovering how (micro-level) SRL processes relate to each other and how they unfold over time. The following paragraph goes into detail about suggestions for theory development.

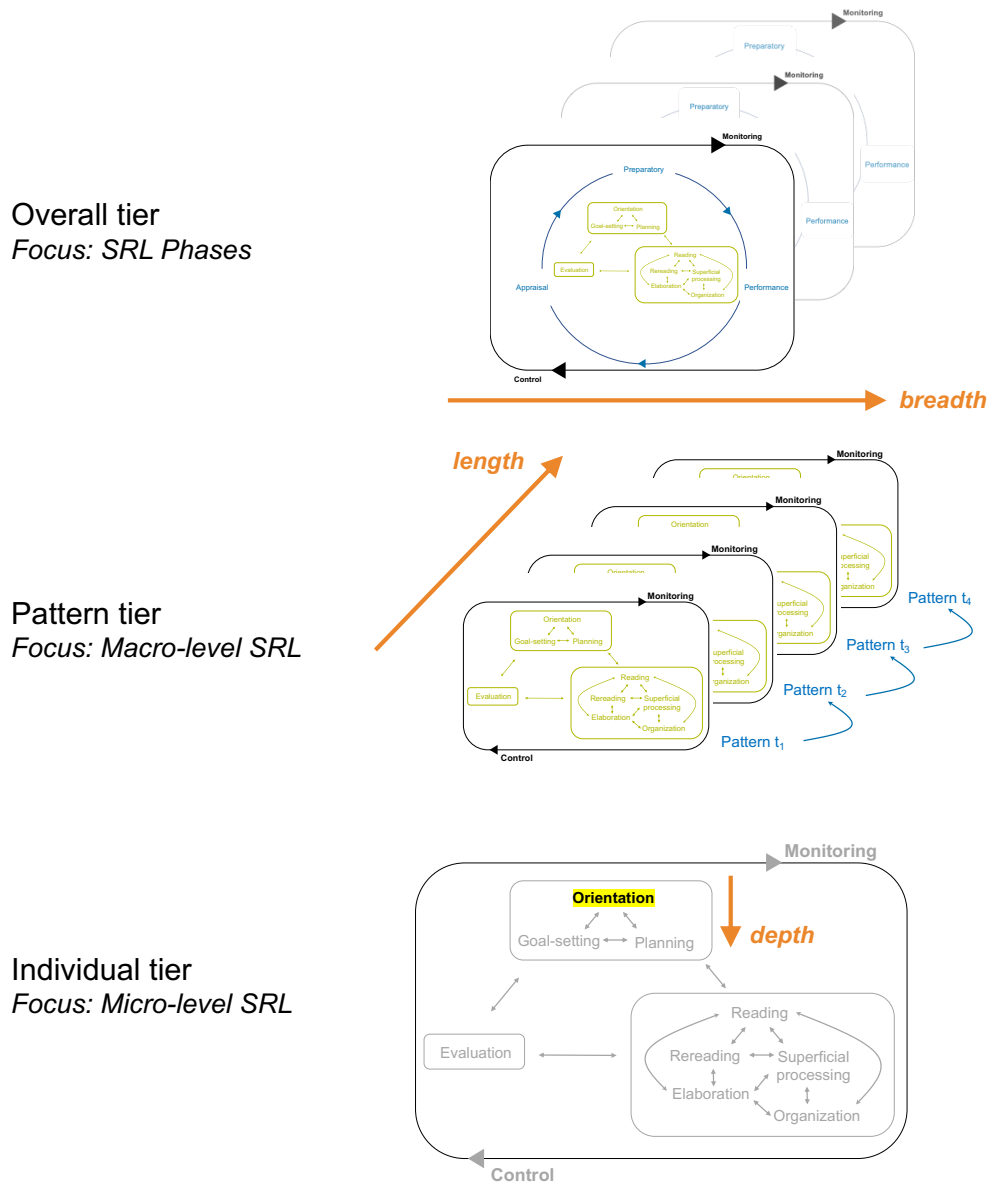
Drawing from the work in this dissertation which investigated SRL at a micro-level, some suggestions for theory development are proposed. This paragraph will use the terms,

“breadth”, “length”, and “depth”, figuratively to elaborate on the suggestions. By modelling SRL processes over the course of a learning session, it is possible to extract how learning occurred in terms of time and sequence. This covers the *breadth* of SRL activities during learning, i.e., what SRL activities students engaged in, when do they engage in these activities, and how they are linked to each other. Hence, looking at the *breadth of SRL* activities allows inferences to be drawn about how these activities are generally carried out. Yet, it is difficult to examine SRL process development because the *breadth perspective* does not consider how activities qualitatively affect (or build upon) each other, i.e., the *length perspective* of SRL (progression). Nelson and Narens’ (1994) conceptualization of the meta- and object-levels of cognition, which they described as multilevel, lends supports to this perspective. According to them, the very first level of processing starts with information obtained only from the object-level, i.e., during monitoring, a mental model (the meta-level) is built based on information from the object-level. As learning continues, subsequent levels obtain information from the immediate previous level, which is also a meta-level for the level before that level, and so forth. In that sense, one’s latter learning activities are affected by their earlier learning activities. This is analogously expressed in the SOI model (Mayer, 1996) and the integrated model of text and picture comprehension (Schnotz & Bannert, 2003), where the three strategies, selection, organization, and integration, build upon each other. For example, when students do not engage in the first strategy or do so sub-optimally, they do not select important information or focus their attention on information which they consider important and relevant, but which are not truly aligned to learning goals, i.e., missing or deficient task analysis. The poor selection likely leads to weakened execution of the second strategy, where (unimportant) information selected are organized in terms of coherence. In the case of an absent selection, students might struggle to organize important information because they have not selected any. Finally, poorly selected or wrong information might consequently be integrated into the long-term memory, leading to incorrect mental model construction. Alternatively, integration does not occur. Nevertheless, Mayer (1996) also states that students can learn to perform the strategies through the teaching of the individual learning strategies. Therefore, in close connection with the *length perspective*, how well each activity is carried out, apart from whether they were carried out or not relates to the *depth perspective*. It can thus be considered as the quality of the activities students engage in. The last paragraph of section 8.4.3 (see Section 8.4.3.2) also discusses this issue of the quality of activities from a practical standpoint. Hence, the figure presented in the beginning

of the dissertation (see Figure 1 in Section 1) is reworked to include the perspectives introduced above (see Figure 7).

Figure 7

Suggestions for theory development and further research perspectives



Note. “Pattern” is used here in a general sense and refers to a group of activities that share some common properties. t₁, t₂, t₃, t₄ are time points.

Bringing together the existing work (Mayer, 1996; Nelson & Narens, 1994; Schnotz & Bannert, 2003) which have discussed the issues individually and empirical support from the findings in the present research, this dissertation proposes that the suggested perspectives

should be made more explicit and tested in order to further contribute to theory development. To test these perspectives, further studies should assess if students who have an optimal start to their learning subsequently perform the latter activities, which are built upon the former, in a more superior manner. In reference to figure 7, how pattern t_1 (i.e., specific groups of activities at time point one) influences pattern t_2 (i.e., specific groups of activities at time point two) and so on with different groups of students (e.g., successful vs. less successful). Furthermore, the quality of micro-level activities should be examined in a closer manner; SRL activities should be coded in terms of quality in addition to quantity. Roelle and colleagues (2017) investigated quality of metacognitive and cognitive activities in addition to frequencies. For example, the quality of cognitive activities such as how coherent mental representations were (i.e., through organization activities). They found that engaging in metacognitive activities prior to cognitive activities led to higher quality of organization activities, despite no differences found in terms of quantity of activities. Linking with an example from the present research, findings from study 1 illustrated that successful students performed learning activities differently than less successful students. There were close connections from monitoring activities to deeper cognitive activities, suggesting that the quality of how these activities performed likely varied between the compared groups.

To conclude, though the current work is considered still within the exploration phase since this was one of the first approaches trying to realize personalized scaffolds and testing their effects, it has provided suggestions for the further development of SRL support with advanced learning technologies as well as theory development. Future investigation into the suggested perspectives potentially provides more understanding as to how students regulate their learning and thus, continues the work to improve SRL support by finding the right balance in terms of recommendations and guidelines.

8.4.2 Methodological implications

The research presented in this dissertation also brings forth some methodological implications. Advanced learning technologies designed upon theory and empirical findings have been shown in the present research to influence learning even in a relatively short time (i.e., a single 45-min learning session). In the case of the research presented, the personalized scaffolding model which included real-time measurement and support of SRL was shown to be the most effective in influencing desired learning activities. Furthermore, the think aloud approach of measuring SRL enabled SRL activities to be recorded at a fine granularity and subsequently facilitated the modeling of SRL patterns in order to distinguish differences

between successful and less successful students. The *post hoc* analyses of the SRL activities of both successful and less successful students guided the identification of general areas for SRL support. The analytics-based SRL measurement protocol, which was validated using the think aloud data (including data from the first study) as a reference point and think aloud coding scheme as theoretical framework¹, enabled SRL gaps, at a micro-level granularity, to be detected in real-time in order for just-in-time personalized scaffolds to be presented. However, there was also much degree of freedom to operationalize the personalization of scaffolds owing to the lack of guidelines. The current personalized scaffolds comprised of the key aspects: adaptivity and scaffold content personalization. A strength in this approach is that the personalized scaffold support is based on students' own learning processes. Although effective to a reasonable extent, the current rule-based AI system is highly dependent on (predetermined) rules and learning context, making it unsuitable to be implemented in unanticipated situations. For instance, when different learning tasks, materials, and contexts are used, parameters have to be adjusted accordingly, and lab studies need to be conducted to test the system as well as personalized scaffolds again. Nevertheless, the real-time analytics-based personalized scaffolding approach used in the present research provided an insight into the infrastructure of such systems and sought to open the door for incorporating other appropriate techniques such as machine learning which are not bounded by the rigidity of rule-based systems.

8.4.3 Practical implications

The next paragraphs discuss the practical implications of the work. The topics and issues addressed can be essentially summarized as the balancing act involved when supporting SRL using advanced learning technologies and raises several topics for subsequent research.

8.4.3.1 Balancing the amount of support provided

The findings from the current research have implications on future SRL support and suggest that the amount of support students need should be investigated further, specifically, do students need less scaffolds or should scaffolds be combined? In the present research, there were strict criteria for the amount of support provided and the personalization of scaffolds. The research presented focused on the content of scaffolds which differentiated support with individual learning activities at critical time points in learning. However,

¹ As the detailed work behind the validation procedure of the analytics-based SRL measurement protocol extends beyond the scope of this dissertation, the reader is encouraged to refer to the paper from Fan, van der Graaf, et al. (2022) for a more comprehensive overview.

findings revealed that already in the control group, students were able to spontaneously engage in monitoring activities though personalized scaffolds enhanced monitoring. This suggests that the amount of support currently provided by the personalized scaffolding model needs to be recalibrated. A highly relevant concept, “HHAIR, Hybrid Human-AI Regulation”, proposed by Molenaar (2022) comes to mind. The HHAIR concept proposes an approach to regulate the support provided by adaptive learning technologies and has the end goal of gradually transferring regulation back to the learner. There is potential in the current personalized scaffolding model to return some amount of control back to the learner from the AI system and focus on consistently low-occurring, but highly important, activities like planning and evaluation. In the framework of the HHAIR concept, this would mean a transition from shared regulation (between the AI and the learner) to self-regulation (by the learner) for at least some of the monitoring activities (e.g., synthesizing both monitoring scaffolds currently provided).

8.4.3.2 Balancing the type of support provided

Findings from the current research have implications on the type of SRL support designed in future studies. There are two aspects of the type of support provided that can be further examined. The first aspect relates to the nature of the personalized scaffolds provided. Winne (2017a) distinguishes just-in-case and just-in-time support. Just-in-case support refers to support provided in the event it is needed and just-in-time support refers to support provided when the need arises. In the work presented here, just-in-time support, initiated by the system and governed by students’ learning processes, was provided to scaffold various activities. Despite the personalized support provided, planning and evaluation activities continue to be difficult to target directly. There is potential to explore using both just-in-case and just-in-time scaffolds for different activities. The MetaTutor system (Azevedo et al., 2016) integrated both user- and system-initiated SRL support and found that combining both self and external regulation was more beneficial in supporting metacognitive processes than only user-initiated SRL, i.e., the control group who received no external support. In terms of just-in-case support, students had access to a SRL palette, providing options to engage in SRL strategies. In terms of just-in-time support, students were also prompted by pedagogical agents who provided scaffolds determined by a complex set of cognitive and metacognitive rules, which was also reported to influence how students self-initiate SRL. The current work could be expanded by integrating components of just-in-case support for planning and evaluation activities. For example, a possible addition should be to include planning scaffolds

within the planner tool, rather than as a pop-up prompt only when necessary. Regarding evaluation, dedicated time at the end of the learning session to review the learning goals and essay rubric should be provided. Currently, the personalized scaffolds include some elements of evaluation (e.g., review the learning goals) within scaffold options and do not address evaluation explicitly yet.

The second aspect of the type of support provided relates to the quality of learning activities students engage in. The current rules in the personalized scaffolding model detect if students have performed specific micro-level activities based on quantity and sequences of learning actions. However, the present version of the AI system does not assess *how* students perform these learning activities. Past scaffold compliance studies (Engelmann et al., 2021; Moser et al., 2017) which further analyzed the use of scaffolds from a qualitative perspective (e.g., with think aloud protocols) found that students who used scaffolds in not only an appropriate (or intended) but also reflective manner (e.g., reflect on past learning activities and how to proceed), reaped their benefits more than students who did not. This provides an opportunity for the current personalized scaffolding model to consider quality of learning activities in the set of rules used. There are two potential research areas to explore further. First, how students interact with scaffolds (e.g., did students process the scaffolds at all or did they close it immediately or select options hastily) should be included in the current set of parameters used to determine support. For example, if students show signs of poor scaffold use, subsequent scaffolds could be adapted by indicating only the top most priority suggestion and/or a short reminder about the purpose of scaffolds to encourage use. Second, assessing quality of learning activities based on the products (i.e., essay, notes, etc.) students create during learning, such as by using automated essay coding facilitated by natural language processing analyses (see Rakovic et al., 2022), and including these information into the current personalized scaffolding model could enable more optimized personalized scaffolds to be provided. It is however essential to note that the learning goal of the task is a key factor in steering the learning activities students engage in and also which activities are deemed more “high quality” for the task at hand. For example, focusing on reading helps with acquiring knowledge but leaves less time for writing. Therefore, the support provided needs to fine-tune to not only the quantity and sequence of SRL activities, but also the quality of activities, as determined by the learning goals.

8.5 Limitations

The research presented encompasses some limitations which should be addressed and considered for future research. The first limitation concerns the study setting. Both studies presented were conducted in strictly controlled laboratory settings. This also means that although internal validity of the studies was high, there was low external validity. In the first study, students were expected to be constantly engaged in the learning task as the experimenter prompted students to think aloud whenever verbalizations ceased for an extended period of time. Although the think aloud approach (i.e., level 2 verbalization/concurrent think aloud) has been found to be a nonreactive method and does not interfere with learning processes (Bannert & Mengelkamp, 2008; Ericsson & Simon, 1984), thinking aloud while learning is atypical in independent learning and could have inadvertently promoted engagement at a higher level than usual. For the second study, an experimenter was likewise present throughout the learning session. This might have prevented some student behavior that could otherwise occur, such as students abandoning the task or seeking additional help. Also, since the learning task was not embedded in the curriculum in authentic settings, students might not have felt a strong reason to improve their learning with the personalized scaffolds. To extend the use of measurement and support approaches presented in this dissertation, further research should be conducted with personalized scaffolds provided within actual course tasks to evaluate their effects as well as increase external validity.

The second limitation concerns the use of one main data channel (i.e., think aloud or trace data) in both studies for the investigation of SRL processes. A number of SRL researchers have proposed the use of multichannel and multimodal data to consolidate observations of SRL (Azevedo et al., 2022; Järvelä et al., 2021; Molenaar et al., 2023). Fan, Lim, and colleagues (2022) have discussed the complementary roles of different data channels, for example, SRL processes were better detected when enriching navigational logs with eye tracking data. However, researchers have also pointed out the challenges involved, as each data channel has its own inherent challenges (Azevedo & Gašević, 2019). For instance, in the first study, unconscious SRL cannot be verbalized (Ericsson & Simon, 1984) and observations of learning made via think aloud protocols are limited in the sense that only active and conscious SRL are considered (see Wirth et al., 2020 for a proposed SRL theory which takes into account unconscious SRL). For the second study, only what was observed via students' interactions with the learning environment was used in interpreting learning behavior but this limits more complete information such as intention and reflection (of

scaffold use). Therefore, researchers in the forefront of the field have advocated the integration of SRL with multimodal data streams along with advanced analytical approaches to better understand SRL and develop SRL research further with the use of AI techniques (Molenaar et al., 2023). Future research should test personalized scaffolds while integrating multimodal data in order to advance the current rule-based AI system with machine learning techniques which are not highly dependent of predetermined rules, and are therefore more flexible.

9 Conclusion

The research presented in this dissertation offered insights to the use and effects of SRL support with advanced learning technologies. This was accomplished through the three action steps set out in the dissertation. By extending prior research to further understanding of how learners (maladaptively or productively) regulate their learning with a focus on SRL measurement, the present research built the basis for fostering the development of SRL scaffolds through theory-driven and empirically-researched decisions. Through the implementation of a personalized scaffolding model based on an analytics approach carried out by real-time measurement and support governed by students' own learning processes, the research presented findings on the effects of SRL support with advanced learning technologies. Furthermore, the dissertation contributes with implications and recommendations for research and practice. Taken together, the research in the dissertation outlines the significance of examining learning processes closely through both measurement and analysis approaches, the critical considerations for real-time adaptive and personalized SRL support, and suggestions on how to go ahead with developing research further on SRL support with advanced learning technologies. Suggestions for theory development are also proposed. To advance the field, interdisciplinary collaboration is vital between the disciplines of learning sciences, educational psychology, learning analytics, computer science and artificial intelligence, and so forth. With the increased integration of sophisticated technologies into different settings, and the swift shift in the landscape of learning especially accelerated by the pandemic, there is great opportunity to develop research further with transdisciplinary research.

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Appendix

Appendix A

Study 1:

Lim, L., Bannert, M., van der Graaf, J., Molenaar, I., Fan, Y., Kilgour, J., Moore, J., & Gašević, D. (2021). Temporal Assessment of Self-Regulated Learning by Mining Students' Think Aloud Protocols. *Frontiers in Psychology, 12*:749749.

<https://doi.org/10.3389/fpsyg.2021.749749>

Appendix B

Study 2:

Lim, L., Bannert, M., van der Graaf, J., Singh, S., Fan, Y., Surendrannair, S., Rakovic, M., Molenaar, I., Moore, J., & Gašević, D. (2023). Effects of real-time analytics-based personalized scaffolds on students' self-regulated learning. *Computers in Human Behavior* 139, 107547. <https://doi.org/10.1016/j.chb.2022.107547>
(published online on 27 October 2022)

Appendix C

Essay coding scheme for both studies

| | Points | Explanation | Examples |
|---|---------------|--|--|
| Topic score <i>Max. 3 points per topic</i> | 0 | No definition, explanation, or explicit application in education | Definition: "AI is is the ability of computers to perform tasks that require humans to use their intelligence, like ..." |
| | 1 | One of: definition, explanation, and explicit application in education | Explanation: "Artificial intelligence essentially consists of two components: a self-learning algorithm and data" |
| | 2 | Two of: definition, explanation, and explicit application in education | Explicit application in education: "Children differ in their abilities, which a teacher can take into account during teaching" (Differentiation) |
| | 3 | All: definition, explanation, and explicit application in education | |
| | Points | Explanation | Examples |
| Connection score <i>Max. 1 point per topic</i> | 0 | No topics mentioned | 1 topic: "AI should be used in future education" |
| | 1 | Mention 1 topic in vision | 2 topics: "AI and scaffolding can be combined when teaching in 2035" |
| | 2 | Mention 2 topics in vision | 3 topics: "Differentiation, AI, and scaffolding are essential for teaching" |
| | 3 | Mention 3 topics in vision | |
| | Points | Explanation | Examples |
| Idea score <i>Max. 1 point per topic</i> | 0 | No suggestions | |
| | 1 | 1 topic used for suggestions for future education | "AI can ask questions and propose suggestions to students. This way teachers will have more time for one-to-one teaching." |
| | 2 | 2 topics used for suggestions for future education | "Children can choose their own topics (differentiation) and when studying it acquire relevant skills while being supported (scaffolding)" |
| | 3 | 3 topics used for suggestions for future education | |

| | Points | Explanation | Information |
|--|---------------|--------------------------------------|---|
| Originality score <i>Max. 3 points in total</i> | 0 | z above 0.5 | From copy scores to z -scores |
| | 1 | z between 0 and 0.5 | Copy scores: 100 means 100% of the essay is a copy of the informative texts |
| | 2 | z between -0.5 and 0 | 0 means no copying and thus, high amount of originality |
| | 3 | z below -0.5 | High z is high amount of copying |
| | Points | Explanation | |
| Word score <i>Max. 3 points in total</i> | 0 | Less than 150 or more than 550 words | |
| | 1 | 150 – 199 or 501 – 550 words | |
| | 2 | 200 – 249 or 451 – 500 words | |
| | 3 | 250 – 450 words | |
| Calculation of scores | 9 | topics (3 x 3) | |
| | 3 | connections (3) | |
| | 3 | idea (3) | |
| | 3 | originality (3) | |
| | 3 | word (3) | |
| Total | 21 | | |