THE EFFORT TO CHANGE

Understanding and Supporting Students' Sustainable Use of Effective Learning Strategies

Louise David

Propositions

1) Students are unlikely to adopt effective learning strategies unless they perceive that the benefits of doing so outweigh the costs (this dissertation)

2) Helping students accurately interpret their perceived mental effort during learning is essential for fostering effective learning (this dissertation)

3) Sustainable change requires alignment with students' goals and with educational contexts that reward long-term learning over short-term performance (this dissertation)

4) Within a course, students' motivation follows a "motivational rollercoaster": motivation is high at the start, declines mid-course, and intensifies again as exams approach, highlighting the strong influence of assessment on self-regulated learning (this dissertation)

5) For complex learning strategies that involve sequential steps and prior preparation, automatizing the initiation of strategy use may be more feasible than automatizing its execution (this dissertation)

6) Using the experience sampling method to capture self-regulated learning in authentic contexts reveals fluctuations in students' study behavior that remain invisible in retrospective measures

7) Sustainable improvement of self-regulated learning requires curricular structures that integrate effective learning strategies within courses rather than leaving their use to students' initiative

8) Teachers play an important role in fostering students' self-regulated learning, not only through instruction, but also by modelling self-regulated learning in their own practice

9) Because self-regulated learning is complex and context-dependent, the design of educational interventions that sustainably change students' study behavior is still in its infancy, and large-scale implementation is premature

10) "We are what we repeatedly do. Excellence, then, is not an act, but a habit." — Will Durant

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DISSERTATION

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Chapter 1

General Introduction

My bachelor's degree in psychology in Maastricht was my first learning experience, during which I had to regulate most of my learning on my own. Without much guidance from others, I had to decide when and how to study. I studied using strategies that I thought were working for me. I prepared shortly before the exam by re-reading summaries, highlighting my notes, and staying up late to cram. While these strategies felt comfortable, I realized that I did not remember much of what I had studied after each course exam. Yet, I continued using them throughout my bachelor's studies and rarely adjusted the way I studied. When I started my PhD, I found myself facing a surprisingly familiar challenge. Without fixed schedules, weekly deadlines, or immediate feedback, I had to rely on my own ability to plan, monitor, and adjust my learning and work habits. Although I now know much more about which regulatory strategies are effective and why, I still struggle to apply them consistently. Planning ahead, breaking tasks into manageable goals, or monitoring progress are skills I have read and written about, and yet in practice, they are challenging to maintain. This tension between knowing and doing has become the central theme of this dissertation. Here, I set out to explore what kind of challenges students experience when using effective learning strategies and how we can support them in integrating these strategies into their daily studying.

Self-Regulated Learning in Higher Education

When aiming for long-term learning, it is essential to self-regulate or steer one's learning effectively. Self-regulated learning (SRL), as conceptualized by Zimmerman (1986), refers to the process by which learners plan and set goals for their learning during the forethought phase, select appropriate strategies and monitor their progress during the performance phase, and evaluate their process and adjust as needed during the self-evaluation phase. For example, when writing the introduction of this dissertation, I started by setting a concrete goal. I wanted to write an outline of the introduction in which I introduce my research topic, connect the most important concepts, and specify my research aims. Before starting, I made a more detailed plan by defining different steps I needed to take to accomplish that goal, such as reading the introductions of the individual chapters again. Throughout writing, I tracked my progress by re-reading what I had written and adding comments wherever I needed to do more work. At the end of each writing session, I reviewed what I had written, noted what worked well (for example, I noticed that taking a walk when I was no longer focused was a helpful strategy for me to continue thinking without getting overly frustrated), and adjusted what did not work by updating my plan for the following session.

Decades of research have shown that self-regulation skills are essential for academic success at all levels of learning (Bjork & Bjork, 2011; Broadbent & Poon, 2015; Dunlosky et al., 2013). Learners who effectively self-regulate their learning tend to achieve better understanding, higher grades, and more durable learning (García-Ros et al., 2023). The importance of self-regulated learning skills increases in higher edu-

cation, where learners have greater autonomy as they need to take control over their studying, deciding what, when, and how to learn outside of classes (Dresel et al., 2015). While university students become more aware of the importance of self-regulated learning skills, many students struggle to monitor and regulate their learning optimally (Biwer et al., 2020; De Bruin et al., 2023). Ideally, students engage in cognitive learning strategies that enhance understanding and long-term retention (such as distributing learning sessions or self-testing), metacognitive strategies that involve planning and monitoring of learning (like setting goals or evaluating learning), and resource management behaviors (such as managing time and study environment). However, instead of using effective strategies necessary for optimal learning, many students struggle to use effective learning strategies and rely on misleading information to monitor their understanding (Biwer et al., 2020; Onan et al., 2022; Rea et al., 2022). For example, instead of using strategies, such as interleaving, self-testing, or distributing learning sessions over time, students often rely on ineffective learning strategies, such as re-reading, highlighting, and summarizing (Biwer et al., 2020; Blasiman et al., 2017; Rea et al., 2022). In the present dissertation, I zoomed in on the gap between learning strategies identified as effective and the ones learners actually use by examining why students often fail to apply effective strategies despite being aware of them, and how students can be supported in using them more effectively during their SRL.

Strategies such as self-testing (or retrieval practice), spacing (or distributed practice), and interleaving are strategies that produce 'desirable difficulties' (Bjork & Bjork, 2011; Bjork, 1994; Bjork & Bjork, 2020). This means that they make learning more effortful while also increasing long-term retention, understanding, and transfer. For example, when using distributed practice, a learner spreads or spaces learning activities over time and repeats learning materials. This is more effective for long-term learning compared to massing study sessions closely in time (e.g., Carpenter et al., 2022; Cepeda et al., 2006; Rohrer, 2015). Distributing one's learning is suggested to enhance long-term learning as the time between study sessions reduces feelings of familiarity or ease towards the material, which in turn causes learners to work more during a next session compared to massed practice which does not have any time in between study sessions (Bahrick & Hall, 2005; Benjamin & Tullis, 2010; Dunlosky et al., 2013). Additionally, the second learning session offers a retrieval opportunity of the learning materials, which strengthens encoding (Benjamin & Tullis, 2010; Dunlosky et al., 2013). Retrieval practice, sometimes called practice testing or self-testing, involves answering questions about material from memory, for instance, via practice tests or flashcards. Research shows that this approach leads to better retention than rereading the information (Carpenter et al., 2022; Carpenter et al., 2008; Dunlosky et al., 2013). One reason is the additional effort that is typically invested when trying to recall information from memory (retrieval effort hypothesis; Kang et al., 2007; Rowland, 2014). Another explanation is that retrieving information activates related knowledge and creates additional memory traces, making it easier to remember later

(elaborative retrieval hypothesis; Carpenter, 2009).

While there is a large portion of research highlighting the effectiveness of desirable difficulties, students struggle to use them during their self-regulated learning and commonly rely on surface-level strategies such as (re-)reading, highlighting, and summarizing (Biwer et al., 2020; Blasiman et al., 2017; Broeren et al., 2024; Hartwig & Dunlosky, 2012; Kornell & Bjork, 2007; Morehead et al., 2016; Rea et al., 2022). While the latter strategies can be important when selecting and organizing information, they do not contribute to long-term learning or transfer of knowledge (Hattie & Donoghue, 2016). In the current dissertation, I set out to investigate why students struggle to use effective learning strategies even if they are aware of them, and how we can support students in using these strategies more sustainably during their self-regulated learning.

Why Students Struggle to Sustain Effective Strategies

Even if students are aware of effective learning strategies, research points to several barriers that make it difficult for students to use them sustainably during their learning. Potential barriers identified relate to 1) the greater mental effort required when using effective learning strategies, 2) misleading metacognitive experiences during learning, and 3) ingrained habits developed during prior education.

First, effective learning strategies often require learners to invest more mental effort compared to passive learning strategies (Bjork & Bjork, 2011; Hui et al., 2022; Kirk-Johnson et al., 2019; Onan et al., 2022). For example, it feels much easier to passively re-read a chapter than to actively quiz oneself on the content. While mental effort is required for learning, individuals are commonly cognitive misers and usually experience effort as aversive and tend to avoid it (David et al., 2024; Kahneman, 1973; Kurzban, 2016; Shenhav et al., 2017).

Second, learners often have misleading metacognitive experiences during learning. As learners do not have direct access to their learning, they usually use indirect information to judge their learning (cue-utilization framework; Koriat, 1997). More specifically, learners typically make study decisions based on perceived learning rather than actual learning (Kornell et al., 2011; Soderstrom & Bjork, 2015). For example, when reading a text, learners must monitor their understanding of a text passage to decide whether to re-read it or move on to the next one. To monitor this understanding, learners use information or cues, such as processing fluency (i.e., how quickly they read through the text) to judge how well they understood it (Kornell et al., 2011). Another cue that learners commonly use is the mental effort required during a task, meaning that they judge their learning based on how effortful the learning activity felt (Baars et al., 2020; Koriat et al., 2014). More specifically, this mental effort experience is usually interpreted as a sign for poor learning (Baars et al., 2020; Hui et al., 2022; Kirk-Johnson et al., 2019; Macaluso et al., 2022; Onan et al., 2022). Another misleading meta-cognitive experience that learners often have is that when using

desirable difficulties, learning effects are often delayed and therefore not immediately evident, which induces low feelings of learning (Bjork & Bjork, 2011; Roediger & Karpicke, 2006). This low perceived learning when using desirable difficulties, either due to misinterpretation of mental effort or learning effects not being immediately evident, biases learners to choose learning strategies that are associated with higher perceived learning and fluency (Hui et al., 2022; Kirk-Johnson et al., 2019; Macaluso et al., 2022; Onan et al., 2022).

Third, students often have strong habits of using surface processing strategies that they acquired during prior education (Dirkx et al., 2019). By the time learners reach university, they have spent years in earlier educational settings developing their own routine ways of studying. If those previous environments did not emphasize active learning strategies and passive strategies helped them pass exams, students often arrive at university with ingrained habits of re-reading notes, highlighting, and massing study sessions closely to the exam (Blasiman et al., 2017; Dembo & Seli, 2004; Foerst et al., 2017). Habits are repeatedly enacted behaviors triggered by a specific context. If this behaviour-context link is sufficiently often repeated, a habit is formed. Now initiation of behavior is automatic and effortless rather than led by deliberate intentions (Gardner, 2015; Lally et al., 2010). On the one hand, this automaticity makes habits powerful as they help to revert to the behaviors that are most practiced and require low conscious effort to initiate. On the other hand, this automaticity makes it very difficult and effortful to change a habitual response. For example, when a learner commonly summarizes chapters to prepare for an exam, reverting to this strategy will feel almost automatic and effortless. Even if the student learns about a better strategy, changing their study habits can be very challenging. For example, Rea et al. (2022) found that university students can recognize which study strategies were most effective in theory, yet they often failed to implement those strategies for their own learning. Students mentioned that this was partially because they were used to certain methods and felt insecure abandoning the study habits that had helped them pass previous courses. Some students even described a kind of automaticity in their approach. Without deliberate planning and especially when time fell short, they would start studying in their routine way (Rea et al., 2022). Thus, beyond having the knowledge about effective learning strategies, university students face several barriers that hinder them from applying these sustainably during their self-regulated learning.

Mental Effort as a Central Barrier to Using Effective Learning Strategies

The barriers as to why students struggle to use effective learning strategies sustainably may seem distinct, yet mental effort emerges as a unifying concept that underlies all three barriers. As introduced above, desirable difficulties, such as retrieval practice or distributed practice, are more cognitively demanding compared to passive strategies like rereading. This increased mental effort commonly feels aversive and can lead to misleading metacognitive judgments. Students may misinterpret the effort expe-

riences when using these strategies as a sign of ineffective learning, leading them to undervalue or abandon them. Furthermore, many students rely on habits involving less effortful, familiar strategies. Shifting away from these established habits requires knowledge and mental effort to break old habits and form new, more effective ones.

Therefore, mental effort is the central concept linking barriers students face when trying to adopt effective learning strategies. It underlies the cognitive demands of effective strategies, the misinterpretation of those demands, and the resistance to changing habitual behaviors. Crucially, the challenge of using effective learning strategies is not only cognitive but also behavioral, as it requires students to repeatedly choose more effortful learning strategies and disregard effortlessly initiated behavior (De Bruin et al., 2023; Fiorella, 2020). Furthermore, to consistently use them, students need to form habits that incorporate these effective learning strategies, which requires additional effort (Verplanken, 2018).

This insight led me to adopt a behavioral change perspective in this dissertation. Although not yet often applied in educational psychology, behavioral change frameworks offer a valuable lens for understanding and addressing the gap between knowing and doing and could help bridge the gap between students' awareness of effective learning strategies and their actual use (Fiorella, 2020). By recognizing that sustained use of effective strategies requires students to engage in intentional, effortful behavior change, we can draw on insights from fields such as health psychology, where similar effort-related barriers have been studied and addressed. In the subsequent section, I introduce why I think this behavioral change approach could be a valuable framework to understand why students struggle to use effective learning strategies, even if they are aware of them, and how insights from behavioral change research could be applied in supporting students to use more effective learning strategies.

Goal-Setting to Initiate Behavioral Change

Numerous interventions have been designed to improve students' awareness and initial use of effective learning strategies (e.g., Ariel & Karpicke, 2018; Biwer et al., 2020; Broeren et al., 2023). Interventions such as the training program Study Smart have proven effective in increasing students' knowledge and raising awareness about what constitutes effective learning (Biwer et al., 2020, 2023). However, their impact on long-term behavior change remains underexamined (Dignath & Veenman, 2021). Most of the intervention approaches concentrate primarily on knowledge acquisition and less on sustained behavioral change (Fiorella, 2020). As a result, although students may try out new strategies shortly after training, many tend to revert to their habitual learning behaviors as the semester progresses, particularly in the absence of ongoing support (Broeren et al., 2024; Rea et al., 2022). In our understanding, study habits relate to commonly repeated behaviors such as the usual length of a student's study session, common learning strategies used, or usual study timing and environment. Since habits are a powerful driver of behavior (Verhoeven et al., 2012; Ver-

planken, 2018), the persistence of ingrained study habits, which include the use of ineffective learning strategies, play a crucial role in whether students maintain new learning strategies over time. In fact, habits are widely considered a key factor in sustaining behavioral change (Rothman et al., 2009; Verplanken, 2018). Therefore, to effectively support students in consistently applying effective learning strategies beyond the initial intervention period, it is crucial to understand and address the role of habits in self-regulated learning (Fiorella, 2020).

Habit Formation for Lasting Change

Incorporating habit-building and behavior maintenance components into SRL interventions seems essential when wanting to support students' sustainable use of effective learning strategies (Fiorella, 2020). For example, by helping a learner develop a consistent habit of creating a few flashcards and reviewing these after each lecture, this could help the learner automate the inclusion of effective learning strategies in their learning over time. However, so far, this perspective is underexplored, and usually interventions focus on increasing knowledge instead of supporting formation of new study habits.

Habits develop by repeating a specific behavior within the same context, eventually creating a strong association between context and behavior (Gardner, 2015; Lally & Gardner, 2013). The goal–habit interface model (Wood & Rünger, 2016) proposes that habits frequently originate from goal-directed actions. To form a habit, first, a specific and measurable objective provides motivational direction for behavior, such as wanting to use more effective learning strategies (Locke & Latham, 2002). Then, this abstract goal is specified into concrete, context-specific steps, often using implementation intentions (e.g., "If it is 7:00 p.m., then I will create and review 10 flashcards") to specify when, where, and how the behavior will occur (Gollwitzer, 1993; 1999). The repeated performance of the planned behavior in a consistent context begins to strengthen cue–response associations (Lally et al., 2010). Once the contextual cues reliably elicit the behavior without deliberate intention, a habit is established, and the behavior transitions from being goal-driven to being triggered directly by contextual cues, independent of the original goal (Mazar & Wood, 2018).

Therefore, goal setting plays a critical role in the early stages of habit formation, as it provides the intentional structure and motivational direction needed to initiate and repeat a desired behavior. Clearly defined goals help individuals translate abstract intentions into specific actions, increasing the likelihood of consistent execution within stable contexts, which is the foundation of habit development (Lally et al., 2010; Wood & Neal, 2007). Moreover, when paired with concrete planning strategies such as implementation intentions, goal setting can enhance the transition from deliberate action to automaticity by linking goal pursuit to situational cues (Gollwitzer, 1999). Thus, while habits may eventually operate independently of conscious goals, the formation of adaptive habits depends strongly on goal-directed processes during their

early development.

The Need for Longitudinal and Contextual Approaches

Bridging the gap between knowing about effective learning strategies and sustaining their use requires research that examines students' behaviors longitudinally and in their authentic learning contexts. Although barriers such as inaccurate self-monitoring, preference for less effortful study strategies, and resistance to change have been investigated, these are often studied in isolation or under controlled experimental conditions. Such controlled designs are valuable for identifying causal mechanisms. General SRL questionnaires give an overall impression of skills (Rovers et al., 2019) but rarely capture the complexity of real academic settings, where multiple barriers interact and are shaped by external influences such as fluctuating motivation, competing demands, and distractions (Breitwieser et al., 2024). In addition, a large body of research has captured students' learning strategies through one-time questionnaires such as the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1993). Such questionnaires provide a snapshot of learners' behavior but fail to give insights into how strategy use develops over time and how it is adapted to task demands or time constraints (De Bruin et al., 2023). These self-reports also vary in accuracy depending on their level of granularity, as there is poor alignment between students' reports on which specific strategies they used and observed behavior (Rovers et al., 2019; Winne & Jamieson-Noel, 2002). These limitations in measurement approaches restrict our understanding of how students adopt effortful strategies across longer periods and why some students abandon them prematurely. To address these limitations, research benefits from longitudinal and more fine-grained methods that track actual behaviors over time within students' authentic learning contexts to capture potential fluctuations in strategy use, motivation, and mental effort. A methodological approach that can provide more nuanced insights but is underused in self-regulated learning research, is the experience sampling method (ESM). When using ESM, participants are repeatedly prompted to report on their thoughts, feelings, or behaviors in real time within their natural environments, enabling to capture processes as they unfold in daily life (Csikszentmihalyi et al., 1977). This way, ESM could provide insights into how learning strategy use evolves, when and why learners struggle to continue using them, and what support might promote sustainably adoption (Breitwieser et al., 2024).

To address this need for more longitudinal and fine-grained insights into students' use of effective learning strategies, the current dissertation integrates qualitative and quantitative approaches to capture students' experiences bottom-up and model their study behavior longitudinally. I aim to provide in-depth insights into when and why students struggle to continuously use effective learning strategies and how we can support students to incorporate them more sustainably within their SRL.

Research Questions

This dissertation aims to identify ways to promote the sustainable use of effective learning strategies in university students' authentic learning settings. To achieve this, I first explored challenges university students face when using effective learning strategies, and secondly, I explored how we can support more consistent use of those strategies within students' self-regulated learning through behavioral change approaches. To address this overarching aim, I formulated the following research questions:

1. How do perceived mental effort and perceived learning relate to actual learning? (Chapter 2)
2. What are students' study habits in higher education and how do they form new and break existing habits within this context? (Chapter 3)
3. To what extent does goal-setting via implementation intentions influence students' self-regulated learning and their use of distributed practice? (Chapters 4 & 5)

Outline of this Dissertation

To answer the research question mentioned above, I conducted four research studies using different approaches.

In chapter 2, I zoomed in on the effort-misinterpretation hypothesis that is often observed in learners, which suggests that as learners cannot access information about their learning directly, they use information such as how effortful their learning feels as an indicator of how well they are learning. However, so far, it is unclear whether perceived mental effort is actually a valid indicator of actual learning outcomes. To better understand whether perceived mental effort is generally a valid indicator of actual learning outcomes, I used a meta-analytic approach to investigate the relationship between perceived mental effort, monitoring judgments, and actual learning outcomes.

In chapter 3, I zoomed in on university students' study habits and how they usually form new and break old habits. I held focus group discussions to gain in-depth understanding of what students' usual study behavior looks like, whether and how they try to change this behavior, and which challenges they face when doing so.

In chapter 4, I describe an intervention study. Using the experienced sampling method, I explored whether implementation intentions can increase students' use of distributed practice. Throughout a four-week university course, I monitored students' daily use of distributed practice as well as other study behavior and attitudes, such as their study motivation, study effort, and study satisfaction. I compared how this differed between students who set specific implementation intentions to incorporate distributed practice compared to students who were merely informed about the benefits of distributed practice and goal-setting.

Chapter 5 extends the findings of chapter 4. Whereas participants in Chapter 4

were randomly assigned to two groups, the present study included three. One group in which participants formulated implementation intentions, one in which participants received only information about distributed practice, and a control group that received neither. Furthermore, I extended the previous design by exploring potential transfer effects during a one-week follow-up ESM period within a new course five weeks later.

In chapter 6, I discuss the studies' findings. I integrated them within the existing literature and discussed implications for educational theory and practical applications. Lastly, I share the theoretical and practical impact of the research undertaken in this dissertation in the impact chapter.

Table 1. Overview of the studies conducted

	Study 1	**Study 2**	**Study 3**	**Study 4**
Aim	Investigate the relationship between perceived mental effort, monitoring judgements, and learning outcomes.	Explore university students' study habits, how they form new and break existing habits.	Investigate the effectiveness of implementation intentions to increase university students' use of distributed practice.	Investigate the effectiveness of implementation intentions to increase university students' use of distributed practice.
Design	Meta-analysis	Focus group discussions	Intervention study with 4-week ESM period to capture study behavior	Intervention study with 4-week ESM period and a 1-week follow-up ESM period to explore longitudinal study behavior
Outcome measures	Learning outcomes	Experiences from students	Self-report questionnaires	Self-report questionnaires
Data sources	Correlations and sample sizes from primary research studies	Transcripts of focus group discussions	Daily study diaries collected via smartphone prompts	Daily study diaries collected via smartphone prompts
Participants	Learners of all ages (N=3973 from 83 independent samples)	University students studying at the Faculty of Health, Medicine & Life Sciences (N=29)	University students studying at the Faculty of Health, Medicine & Life Sciences (N=87 with k=1623 observations)	University students studying at the Faculty of Health, Medicine & Life Sciences (N=100 with k=1998 observations)

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Chapter 2

The Relation Between Perceived Mental Effort, Monitoring Judgements, and Learning Outcomes: A Meta-Analysis

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Abstract

Accurately monitoring one's learning processes during self-regulated learning depends on using the right cues, one of which could be perceived mental effort. A meta-analysis by Baars et al. (2020) found a negative association between mental effort and monitoring judgments (r = -.35), suggesting that the amount of mental effort experienced during a learning task is usually negatively correlated with learners' perception of learning. However, it is unclear how monitoring judgments and perceptions of mental effort relate to learning outcomes. To examine if perceived mental effort is a diagnostic cue for learning outcomes, and whether monitoring judgments mediate this relationship, we employed a meta-analytic structural equation model. Results indicated a negative, moderate association between perceived mental effort and monitoring judgments (β = -.19), a positive, large association between monitoring judgments and learning outcomes (β = .29), and a negative, moderate indirect association between perceived mental effort and learning outcomes (β = -.05), which was mediated by monitoring judgments. Our subgroup analysis did not reveal any significant differences across moderators potentially due to the limited number of studies included per moderator category. Findings suggest that when learners perceive higher levels of mental effort, they exhibit lower learning (confidence) judgments, which relates to lower actual learning outcomes. Thus, learners seem to use perceived mental effort as a cue to judge their learning while perceived mental effort only indirectly relates to actual learning outcomes.

Keywords: mental effort, monitoring, performance, metacognition, meta-analysis, cue-utilization

Knowing how to study and steer, or self-regulate, one's learning process effectively is a key skill in education (Broadbent & Poon, 2015). Even if not being formally taught how, learners often have to make decisions when it comes to their learning behavior. For example, they have to decide whether to re-read a text, which learning task to do next, or which learning strategy to use when memorizing content. To optimize learning outcomes, accurately monitoring learning and—based on this monitoring—accurately regulating one's learning process is essential (De Bruin & Van Merriënboer, 2017; Dunlosky & Rawson, 2012). However, many learners struggle to accurately monitor their learning process, leading them to make suboptimal study decisions (e.g., Baars et al., 2013, 2014; Bjork et al., 2013; Butler & Winne, 1995; Cavalcanti & Sibbald, 2014; Dinsmore & Parkinson, 2013; Kostons et al., 2012), which hampers learning and, consequently, academic outcomes (Dunlosky & Metcalfe, 2009; Dunlosky & Rawson, 2012; Kanfer & Ackerman, 1989). In the current manuscript, we use the term learning outcomes as quantifiable achievements or performances displayed by learners following a learning phase. These outcomes usually refer to knowledge acquisition, which is demonstrated shortly after the learning phase on a near-transfer task.

Given that learners often cannot access information about their learning outcomes directly, they usually monitor their learning outcomes based on indirect information or cues (i.e., cue-utilization framework; Koriat, 1997). More specifically, learners use various cues, such as processing fluency or perceived mental effort, to inform their metacognitive monitoring (Baars et al., 2020; Koriat & Ma'ayan, 2005; Koriat et al., 2006; Koriat, Nussinson, & Ackerman, 2014; Onan et al., 2022; Undorf & Erdfelder, 2011). Using a meta-analytic approach, Baars and colleagues (2020) found a negative, medium-sized correlation (r = -.35) between effort and monitoring judgments. This negative correlation suggests that greater perceived effort is often linked to lower estimates of learning, whereas lower perceived mental effort tends to correspond with higher estimations of learning. This pattern implies that learners might use the amount of effort they expend as a cue to guide their monitoring of learning judgments, which we will refer to as 'monitoring judgments' going forward. More specifically, if learners experience high mental effort when working on a task, they could interpret this as a sign of poor learning. However, it is unclear to what extent perceived mental effort is associated with actual learning outcomes and, therefore, it is unclear to what extent perceived mental effort is diagnostic for actual learning outcomes. If indeed perceived mental effort is used as a cue for making monitoring judgments, but perceived mental effort is not associated with learning outcomes, this could lead to inaccurate monitoring judgments. Subsequently, this could influence learners to take ineffective learning decisions, decreasing their learning and academic outcomes. Therefore, it is crucial to investigate the relationship between perceived mental effort, monitoring judgments, and learning outcomes. Furthermore, investigating if perceived mental effort acts as a diagnostic cue for learning necessitates examining its relationship with learning outcomes. Following the cue-utilization

framework as conceptualized by Koriat (1997) and interpreted by De Bruin and Van Merriënboer (2017), it is crucial to determine whether monitoring judgments mediate this relationship. In case of a negative indirect effect between perceived mental effort and learning outcomes, we would interpret this as perceived mental effort being used as a negative cue for perceived learning, or confidence herein, which in turn are positively related to learning outcomes. Hence, using a meta-analytic approach, the current study investigated the relationship between learners' perceived mental effort, monitoring judgments, and learning outcomes.

Importance of Accurate Monitoring in Self-Regulated Learning

Self-regulated learning is a crucial skill in education. Learners are exposed to learning environments where they must plan, monitor, and regulate their learning process. They have to make regulatory decisions according to their learning outcomes and comprehension and, for example, decide whether to re-read a text or choose which learning strategy to use for a specific task. For optimal behavioral regulation and adaptation in accordance with learning, it is imperative that learning progress is accurately monitored (De Bruin & Van Merriënboer, 2017; Dunlosky & Rawson, 2012).

Learners often cannot access their learning outcomes and knowledge directly and, therefore, usually make inferences about their learning outcomes based on indirect information or cues (Koriat, 1993, 1997). According to the cue-utilization framework (Koriat, 1997), three elements are involved in self-regulated learning: cues, monitoring judgments, and actual learning or performance. Learners utilize cues arising from their study experiences or materials to formulate a monitoring judgment, which is called cue-utilization (Koriat, 1997). The extent to which cues predict learning outcomes and are, therefore, diagnostic is termed cue diagnosticity (Brunswik, 1956). The extent to which a monitoring judgment accurately predicts learning outcomes is often coined monitoring accuracy (Butler & Winne, 1995; Nelson, 1984; Schraw et al., 2009). Often, learners utilize cues to self-regulate their learning process, which are not indicative of actual learning outcomes, meaning that the cues are not diagnostic. This use of non-diagnostic cues thus leads to inaccurate monitoring (De Bruin et al., 2017; Koriat, 1993, 1997; Thiede et al., 2010).

Perceived Mental Effort as a Cue for Monitoring

Learners use various cues such as processing fluency of the learning process, previous task-specific experiences, or perceived mental effort experienced during learning to inform their metacognitive monitoring (e.g., Baars et al., 2020; Koriat & Ma'ayan, 2005; Koriat, Nussinson, & Ackerman, 2014; Onan et al., 2022; Undorf & Erdfelder, 2011). In the memorizing effort heuristic, Koriat et al. (2006) suggested that perceived mental effort, or invested study time, is often utilized as a cue for metacognitive judgments. That is, learners operate under the assumption that the items they learned with less mental effort exertion are easier to recall compared to those that re-

quired more effort (the "easily-learned-easily-remembered" heuristic; Koriat et al., 2006). Here, interpretation is driven by learners' own perception of effort, which is also referred to as a data-driven interpretation of effort (Koriat, Nussinson, & Ackerman, 2014). This results in a negative relationship between perceived mental effort and monitoring of learning outcomes (e.g., Baars et al., 2013, 2018, 2020; Koriat et al., 2009; Undorf & Erdfelder, 2011).

Interestingly, research indicates that the correlation between mental effort and monitoring does not necessarily need to be negative (Baars et al., 2020; Koriat, 2008; Koriat et al., 2006, 2014b). For example, if learners value learning about a topic or have a salient goal to achieve when investing mental effort, there is a positive or zero-order relationship between mental effort and monitoring judgments, meaning that more mental effort is related to higher perceived learning or certainty of knowing (in case of a positive association). Here, the metacognitive judgments are regarded as goal-driven, and learners invest mental effort in accordance with the importance or interest of the to-be-learned materials (Koriat, Ackerman, et al., 2014). So far, goal-driven self-regulation has been manipulated by inducing time pressure, providing incentives (e.g., Ackerman, 2014; Koriat et al., 2006), or by increasing learners' sense of agency by changing the wording of the mental effort self-rating scale such as asking about the invested mental effort instead of the required mental effort (Klepsch & Seufert, 2021; Koriat, Nussinson, & Ackerman, 2014).

The finding that the correlation between mental effort and monitoring does not necessarily need to be negative is supported by the meta-analysis by Baars and colleagues (2020). While they found an overall negative, medium-sized correlation between effort and monitoring judgments ($r = -.35$), their moderator analysis results showed that this association was no longer significant for studies employing goal-driven manipulations, such as incentives, time pressure, or promoting feelings of self-agency (Baars et al., 2020). While the response to goal-driven manipulations and improvement in cue-utilization has been shown to develop with increasing age (Hoffmann-Biencourt et al. 2010; Koriat et al., 2009; Koriat, Nussinson, & Ackerman, 2014), Baars and colleagues (2020) did not identify learners' age or level of education as significantly moderating the relationship between effort and monitoring judgments. Contrastingly, Baars and colleagues (2020) identified type of task as a significant moderator with a higher negative correlation in studies using problem-solving tasks compared to other tasks such as word learning or paired associates.

An additional factor potentially influencing the relationship between perceived mental effort and monitoring judgments could be task difficulty (Seufert, 2018). During tasks that are more difficult learners might have fewer available cognitive resources to accurately monitor their learning process compared to easier tasks (Seufert, 2018). It is therefore interesting to explore whether task difficulty moderates the relationship between perceived mental effort and monitoring. Collectively, these studies suggest that perceived mental effort might be used as a cue to self-regulate one's learning. Depending on students' effort interpretation (data- or goal-driven) per-

ceived mental effort may have positive or negative effects on students' monitoring of learning, and thus on their learning outcomes. To unravel the potential relationships between perceived mental effort, monitoring, and learning outcomes, the current study aimed to provide more insight into how perceived mental effort is used as a cue to monitor learning, how that, in turn, affects learning outcomes, and what factors moderate these relationships.

Monitoring Judgments and Learning Outcomes

Learners often face challenges in accurately monitoring and regulating their learning without supplementary aid (e.g., Baars et al., 2014, 2013; De Bruin et al., 2011; Dunlosky & Lipko, 2007; Prinz et al., 2020a; Van Gog et al., 2020), primarily due to a tendency to overestimate their own learning outcomes (Baars et al., 2013, 2014; Baars & Wijnia, 2018). This is potentially due to the additional mental effort that is required to simultaneously fulfill the task demands and monitor learning outcomes (Van Gog et al., 2011, 2020) as well as using the wrong cues to infer learning (Koriat, 1997). Especially in complex tasks, learners tend to inaccurately monitor their learning outcomes compared to less complex tasks (Baars et al., 2018). Several generative strategies have been shown to increase learners' monitoring accuracy. In particular, activities such as generating keywords, summaries, or diagrams when reading a text, have been indicated to improve learners' monitoring accuracy because they aid learners in gaining access to more diagnostic cues (for a review, see Prinz et al., 2020b).

To measure the accuracy of a monitoring judgment in relation to learning outcomes, several measures of relative or absolute accuracy can be used (see Schraw, 2009). Relative monitoring accuracy indicates the degree to which learners can discriminate between well-learned and less well-learned materials (Maki & Berry, 1984; Nelson, 1984) and is the relationship of interest in this manuscript. Relative accuracy is typically calculated by a correlational measure (Schraw, 2009). The higher the positive correlation between a learner's estimation of learning outcomes and their actual learning outcomes, the higher their monitoring accuracy. A low positive correlation coefficient indicates low monitoring accuracy. A negative relationship between a learner's monitoring judgment and their actual learning outcomes indicates inaccurate monitoring.

Absolute accuracy refers to the discrepancy between a monitoring judgment and actual learning outcomes and indicates the extent to which learners are able to accurately estimate their absolute level of learning outcomes (Schraw, 2009). If a learner estimates their learning outcomes higher than their actual learning outcomes, overconfidence is observed. Underconfidence is observed when learning outcomes exceed learners' estimation of their learning outcomes.

Monitoring judgments are usually assessed using various self-report items with different scales (e.g., from 1 to 5, 1 to 7, or in percentages from 0% to 100%; Dunlosky & Metcalfe, 2009). There can also be variations in the timing of monitoring judgments. They can be examined prospectively, concurrently, or retrospectively (Schraw,

2009). For example, prospective judgments such as ease of learning judgments (EOLs) aim to measure learners' predictions of how easy it will be to learn information, while judgments of learning (JOLs) aim to measure learners' prediction of how well they think they will recall just-learned information at a later time. These judgments are usually made prior to the task that is judged. Concurrent judgments are made whilst performing the task. Commonly, they are administered on an item-by-item level immediately after learners answer an item of the to-be-judged task (Schraw, 2009). Examples are online confidence ratings, ease of learning judgments, or online learning outcome predictions investigating how confident a learner is in their learning outcomes, how easy it was to work on the task, or how accurate they estimate their learning outcomes (Schraw, 2009). Retrospective judgments are usually made after fully completing the task that is judged. They can refer to an item-by-item level but also to a global task level. Examples are similar to the concurrent judgments (i.e., confidence ratings, ease of learning judgments, or learning outcome accuracy judgments) only that they are administered after all items of the to-be-judged task are completed (Schraw, 2009).

While the type and timing of monitoring judgments significantly vary across the field, dictated by the research question, study design, and target population, it has been established that the timing of these judgments directly impacts their accuracy (Leonesio & Nelson, 1990; Siedlecka et al., 2016). When comparing the accuracy of prospective and concurrent[1] confidence judgments, Siedlecka and colleagues (2016) found that the relationship between confidence and learning outcomes was weaker for prospective confidence ratings. A potential reason for this could be that a learner has less available information to base their metacognitive judgment on compared to judgments that are given concurrently (Siedlecka et al., 2016). Similarly, Baars and colleagues (2020) found that both type and timing of monitoring judgments significantly moderated the relationship between effort and monitoring. They found a weaker correlation for studies administering prospective JOLs compared to other judgments and a weaker correlation for studies administering prospective compared to concurrent judgments (Baars et al., 2020).

Mental Effort and Learning Outcomes

Previous work has established that mental effort is related to monitoring and could thus potentially be used as a cue (Baars et al., 2020). Yet, it remained unclear to what extent perceived mental effort might be a diagnostic cue for monitoring. Mental effort is an essential indicator of cognitive load (Paas et al., 2003; Sweller et al., 1998, 2019), and effortful processing is necessary for explicit learning (e.g., Bjork & Bjork, 2011). A positive relationship exists between effortful processing and learning outcomes as long as the learning task requirements are within the limits of working memory capacity and the cognitive effort necessary for processing and integrating information is directly relevant to learning. However, when the effort required to handle the learning task surpasses these boundaries, learning falls short, and the relation-

[1] Although Siedlecka et al. (2016) indicated to have used retrospective judgments, in line with Schraw (2009), we would operationalize them as concurrent judgments.

ship between effortful processing and task performance becomes negative. For tasks within these cognitive limits, and depending on the complexity of the task, various strategies exist to further enhance learning (Chen et al., 2018, 2023). For complex tasks, this can be done by substituting information that is relevant for the learning task for information that is not relevant (Paas & Van Merriënboer, 2020; Sweller et al., 2019). For less complex tasks, relevant information can be added to the task (i.e., increased intrinsic cognitive load) or learners can be encouraged to invest more effort into available relevant information (i.e., leveraging desirable difficulties; De Bruin et al., 2023).

Next to mental effort, mental load and task performance are also discussed as important indicators of cognitive load in the literature (Paas & Van Merriënboer, 1994). Mental load is commonly seen as learners' cognitive resources, which are required to meet the task affordances in a bottom-up manner and is usually independent of learners' characteristics such as prior knowledge or expertise, increasing with task complexity. This is often also referred to as data-driven effort (Koriat et al., 2006) which learners experience passively (Seufert, 2018; for an overview, see Scheiter et al., 2020). Mental effort involves the active investment of learners' resources to fulfill the demands of a task, and this is shaped by the learner's attributes, the nature of the learning task, the context of the learning environment, as well as the interplay among these factors (Choi et al., 2014; Paas & Van Merriënboer, 1994). Additionally, mental effort can have a motivational component (Feldon et al., 2019; Paas et al., 2005; Scheiter et al., 2020) and is also referred to as goal-driven effort (Koriat et al., 2006). For example, based on learners' estimated success in reaching certain learning outcomes they might be willing to invest more or less effort when working on a task.

Learning outcomes are influenced by the mental load and mental effort a task elicits and learners' individual characteristics such as their prior knowledge or willingness to invest mental resources (Paas & Van Merriënboer, 1994). For example, if task complexity is high, a task imposes high mental load on the learner and more mental effort investment is necessary to perform well on the task, compared to a less complex version of the task. Learners have to take into account their self-assessed learning outcomes to regulate their effort investment accordingly and, for example, invest additional mental effort, switch to a different learning strategy, or ask for external help (De Bruin et al., 2023).

Mental effort can be measured in multiple ways. On the one hand, there are physiological measures such as heart rate variability, pupil dilation, or skin conductance rate (for an overview, see Ayres et al., 2021), or behavioral measures such as response time or time on task. On the other hand, there are subjective measures using self-report scales. In the current study, we are interested in perceived mental effort due to it being a salient cue that learners might experience during their self-regulated learning (Bruin et al., 2023). The subjective character usually represents learners' self-assessed experience of mental effort and thus provides valuable insights into learners' experiences during learning. A commonly used item in educational science is the Paas-scale

(Paas, 1992), in which learners are asked to judge the amount of mental effort they invested on a 9-, 7-, or 5-point Likert scale ranging from "very, very low mental effort" to "very, very high mental effort" (for an overview see Paas et al., 2003). This scale, proven to be user-friendly, valid, and reliable (e.g., Paas et al., 1994), exhibits even higher construct validity than physiological measures, as suggested by the recent review by Ayres et al. (2021).

While the timing of administering these ratings varies in the field, it has been indicated that timing influences the ratings and their predictability of learning outcomes (Schmeck et al., 2015; Van Gog et al., 2012). Compared to an average of mental effort ratings administered multiple times during a learning task, a single delayed mental effort rating at the end of a series of tasks was higher (Schmeck et al., 2015; Van Gog et al., 2012). This suggests that timing or reference level of mental effort ratings influence the relationship between perceived mental effort and learning outcomes and thus the diagnosticity of mental effort as a cue.

Relationship Between Mental Effort, Monitoring, and Learning Outcomes

According to models of self-regulated learning (e.g., Panadero, 2017), monitoring processes inform regulation processes which in turn affect learning outcomes. Earlier research has shown that mental effort is related to monitoring (e.g., Baars et al., 2020) which suggests that mental effort can be used as a cue for monitoring. This means that, theoretically, mental effort can have an indirect effect on learning outcomes via monitoring processes. That is, learners can use their perceived mental effort to make monitoring judgments, which in turn affect regulation of learning and learning outcomes.

Evidence exists that mental effort, monitoring judgments, and learning outcomes are related in learning tasks. Blissett and colleagues (2018) investigated the triangle between mental effort, monitoring, and learning outcomes in medical reasoning. They investigated the cue-utilization of perceived mental effort, how diagnostic mental effort is as a cue for monitoring, and the monitoring accuracy of certainty judgments. Their findings indicated that mental effort is used as a cue for certainty judgments. Furthermore, they identified mental effort as a diagnostic cue: Higher perceived mental effort was associated with lower learning outcomes. Additionally, they found that monitoring was moderately accurate as higher certainty was related to higher learning outcomes. While this study gives a first insight into the relationship between perceived mental effort, monitoring, and learning outcomes, it is unclear what this relationship looks like when combining multiple studies and when taking into account possible moderators. Knowing to what extent perceived mental effort relates to learners' learning outcomes will indicate whether perceived mental effort is a diagnostic cue for learning outcomes and whether and when learners should use their perceived mental effort as a basis to self-regulate their learning. Also, to understand the role of

mental effort in self-regulated learning, it is important to investigate the indirect relationship between mental effort and learning outcomes via monitoring. Given the specific relationships of interest described above and the availability of multiple studies investigating these, a meta-analysis is a promising approach to this question.

The Present Study

Using a meta-analytic approach, we investigated the relationship between perceived mental effort, monitoring judgments, and learning outcomes. Our goal was to take a triangular approach to the cue-utilization framework (De Bruin et al., 2017; Koriat, 1997). Therefore, we specified perceived mental effort as a cue, monitoring of learning judgments as monitoring judgments, and learning outcomes as an approximation of actual learning or performance to understand how they collectively contribute to metacognitive processes. We analyzed the relationships simultaneously by including the paths and variables of interest in a comprehensive model. We first tested whether we could replicate a medium, negative relationship between perceived mental effort and monitoring judgments (i.e., cue-utilization; Baars et al., 2020). We expected a negative relationship between mental effort and monitoring judgments (of perceived learning; Hypothesis 1). For example, we expected that if a learner judges their perceived mental effort to be high, they will judge their perceived learning (reflected by the monitoring judgment) as low. Second, we investigated whether there is a positive relationship between monitoring judgments and learning outcomes (i.e., monitoring accuracy). We expected a positive relationship between monitoring judgments and learning outcomes (Hypothesis 2). For example, we expected that if a learner judges their perceived learning (reflected by the monitoring judgment) as high, learning outcomes during the task would also be high. Third, we wanted to explore whether the relationship between perceived mental effort and learning outcomes (i.e., cue diagnosticity) is mediated by monitoring judgments. We expected monitoring judgments to mediate the relationship between mental effort and learning outcomes (Hypothesis 3) due to the central role of monitoring in self-regulated learning. A negative indirect effect (with a negative direct effect between perceived mental effort and monitoring judgments and a positive direct effect between monitoring judgments and learning outcomes) would indicate that when learners experience high mental effort, this is associated with lower feelings of learning or confidence, which in turn would also relate to actual lower learning. Furthermore, as we expected that certain sample and task characteristics would influence the magnitude of the relationship between mental effort, monitoring judgments, and learning outcomes, we conducted various subgroup analyses to investigate moderating effects of learners' level of education, the formulation and timing of mental effort measurements, types and timing of monitoring judgments, type of task, task difficulty, and whether goal-driven manipulations were used (Hypothesis 4).

Method

Transparency and Openness

We pre-registered our hypotheses, procedure, coding scheme, and analysis plan on the Open Science Framework (OSF) website https://osf.io/u4dgt (pre-registration). Our data set can be found on OSF via https://osf.io/hc5fk/.

Inclusion Criteria

1. Document type. We included published, peer-reviewed texts as well as unpublished texts that were written in English (i.e., grey literature such as conference proceedings, dissertations, and master theses). In addition, unpublished data were included.
2. Sample size. We only included samples with $N > 10$ per independent sample to make sure to include relatively robust studies. If an article reported multiple independent samples, we coded these samples separately.
3. Participants. We only included samples of participants who were healthy and had no psychological variations (e.g., ADHD, autism) and were not under the influence of a severe pharmacological or psychological treatment (e.g., drug administration, induction of stress or mental fatigue, sleep deprivation; e.g., Sugden et al., 2019).
4. Mental Effort. We focused on perceived mental effort and, therefore, excluded studies that only reported other mental effort indicators such as response time, time on task, or physiological measures such as pupil dilation (e.g., Huh et al., 2019; Koriat & Nussinson, 2009).

Method. We only included studies in which the (cor)relation between perceived mental effort, monitoring judgments, and learning outcomes and the sample size were reported or received after a request via email to the corresponding author. Also, only studies were included in which perceived mental effort, monitoring judgments, and learning outcomes were measured on a quantitative scale in the context of a learning outcome of a learning task. Furthermore, perceived mental effort, monitoring, and learning outcomes had to be measured in one study or experiment in the same trial for the same item or criterion task for a study to be included. Between-subjects conditions were coded separately, but if perceived mental effort, monitoring, and learning outcomes were measured multiple times under varying conditions for the same group of participants (i.e., within-subjects design), we did not code these conditions separately but used the mean correlation in our analysis.

Systematic Search Strategy

We searched the Maastricht University Web of Science (WOS) Core Collection, PubMed, and the CINAHL, ERIC, LISTA, APA PsycInfo, SocINDEX, and Open-

Dissertations databases within EBSCOhost. The WOS Core Collection included the Science Citation Index Expanded (1988–present), Social Sciences Citation Index (1988–present), Arts & Humanities Citation Index (1988–present), Conference Proceedings Citation Index – Science (1990–present), Conference Proceedings Citation Index – Social Science & Humanities (1990–present), and the Emerging Sources Citation Index (2018–present). We searched the full text of articles and used the following search terms (ALL ("mental effort" OR "perceived effort" OR "subjective effort" OR "experienced effort" OR "cognitive effort" OR "cognitive load" OR "mental load" OR "germane load" OR "intrinsic load" OR "extraneous load" OR "working memory load")) AND (ALL (monitor* OR "judg* of learning" OR "confidence judg*" OR "confidence rating*" OR "metacognit* judg*" OR "latency-confidence" OR "perceived learning")) AND (ALL (learning OR "self regulat*" OR "metacogniti*" OR "accuracy" OR "diagnostic*" OR "perform*" OR "learning outcome" OR "cue utili*")). We restricted the results to only including documents published from 2000 onwards to maintain the relevance of results. Additionally, the influential cue-utilization framework (Koriat, 1997) underlying the majority of relevant studies was published in 1997, which is why we did not expect many relevant studies before 2000. Additionally, by limiting our search to include primarily recent research, we anticipated a greater homogeneity in the methodologies and technologies used across the studies. Our search yielded 1691 total hits, with 735 hits from WOS, 605 hits from EBSCO, and 351 hits from PubMed. More details can be found in a PRISMA flow chart adapted from Page and colleagues (2021) in the supplementary material.

We applied our inclusion criteria in two steps. First, we screened the articles, checking whether the article reported mental effort ratings, monitoring judgments, and a learning outcome measure using the website Rayyan.ai (Ouzzani et al., 2016). In the second step, we checked the remaining inclusion criteria of the articles that measured the three variables.

Included Variables and Effect Sizes

Our key outcome of interest was participants' learning outcome. We operationalized the variable as the actual learning or performance on a learning task, such as the number of correct answers on a test (e.g., Mihalca et al., 2017) or number of correct solution steps in a problem-solving task (e.g., Baars et al., 2014). The main independent variables were perceived mental effort and monitoring judgments. Both variables were measured with self-report items. Perceived mental effort, which usually represents learner's self-assessed experience of mental effort, was usually measured using the Paas-scale (Paas, 1992), in which learners are asked to judge the amount of mental effort they invested on a 9-, 7-, or 5-point Likert scale ranging from "very, very low mental effort" to "very, very high mental effort." Monitoring judgments, which usually are a form of learners' self-assessment of their learning, such as judgments of learning or confidence ratings, are often measured by asking participants to indicate how

likely they are to remember studied information on a later test. Often these monitoring judgments, such as JOLs, feeling of knowing, or ease of learning judgments, are answered by indicating one's estimated likelihood to later recall the information on different scales (e.g., from 1 to 5, 1 to 7, or in percentages from 0% to 100%; Dunlosky & Metcalfe, 2008). As mentioned above, the type and timing of monitoring judgments and perceived mental effort ratings can vary.

To perform the meta-analysis, we collected the Pearson's correlation coefficient between perceived mental effort, monitoring judgments, and learning outcomes as reported by other researchers. If a study measured various types of the variables of interest such as ease of learning and JOLs (e.g., Beege et al., 2021), we chose the type that was most commonly used in other studies, which were JOLs. We coded between-subjects conditions as independent samples (e.g., in the study by Baars et al. [2014] the learners in the self-assessment training condition and learners in the no self-assessment training condition were coded as separate samples) and coded all variables on the task level (i.e., each data point reflected a group of people that carried out the same task). If the correlations were not reported in the paper, we contacted the corresponding authors. We extracted or received the Pearson's correlation coefficient and accompanying sample size from 35 papers, with 83 independent samples, and 236 effect sizes. The effect sizes consisted of 83 correlations between mental effort and monitoring, 77 correlations between monitoring and learning outcomes, and 76 correlations between effort and learning outcomes. Based on the correlation coefficient and sample size, we estimated the sampling variances with the rma.mv function of the metafor package (Viechtbauer, 2010) in R (R Core Team, 2021).

Coding

Procedure

Table 1 represents the clustering of moderators we used in our analysis. LD, FB, MB, and LW coded the moderators and control variables of the articles. To facilitate the reproducibility of the coding, we created a detailed coding scheme before data extraction. For calibration purposes and to examine the coding scheme's fit to the articles, all coders coded the same five articles. Coding differences were discussed and resolved, and when necessary, the coding scheme was adjusted or the interpretation of coding categories was further clarified. After this calibration phase, 49 samples (corresponding to 59% of the total data) were coded by two raters to estimate the alignment of the coding. To assess inter-rater reliability, we calculated Cohen's k for categorical variables, which ranged from k = .30 (fair) to k = 1 (perfect) with a mean of k = .77 (substantial; Landis & Koch, 1977). After discussing the results and coming to an agreement and included additional examples in our coding scheme to improve clarity. Our final coding scheme is available at OSF.

Table 1. Overview of Moderator Variables

Moderator		Description (number of studies)
1.	Education	Higher & Post Education (165); Other levels of education (55)
2.	Mental Effort Measurement	Mental effort rating (167); Other types of effort ratings (69)
3.	Mental Effort Wording	Active (166); Other (70)
4.	Effort Reference	Item-by-item (146); Global task (90)
5.	Type of Monitoring	JOL (169); Other (67)
6.	Monitoring Timing	Prospective (157); Concurrent (76)
7.	Monitoring Reference	Item-by-item (125); Global task (111)
8.	Type of Task	Problem-solving (98); Other tasks (138)
9.	Task Difficulty	Not specified (157); Other (79)

Note. The Description column reports all moderator categories that we included in our analysis. To our knowledge, the analytic approach we chose only allows for subgroup analysis, which is why we merged categories with small numbers of effect sizes per moderator to create two groups. Certain moderators did not have enough variability within their categories, which is why we decided against analyzing them. The categories and excluded moderators are not included in this table but are described in the main text. The number in brackets represents the number of effect sizes in the category and is referred to as k in the main text.

Moderators

Level of Education. If reported, we coded the sample's average level of education based on the authors' categorization. The majority of measurements came from samples in higher education (k = 152), followed by 9th grade (k = 26), 8th grade (k = 18), postgraduate education (k = 13), 3rd grade (k = 6), and 4th grade (k = 5). For 13 effect sizes, no level of education was mentioned (k = 13). If there were participants from multiple levels of education included in the study, then we coded the level of education of the majority of participants. If participants were spread across levels of education, then we coded the sample's mean level of education. For the subgroup analysis, we compared effect sizes from samples within higher or postgraduate education to samples from all other levels of education.

Mental Effort Measurement. We coded the type of mental effort measurement. The majority of measures were conducted using a mental effort rating such as the Paas-scale (k = 167; Paas, 1992) followed by effort ratings (k = 42), other ratings (k = 22), and judgments of difficulty (k = 5). We coded effort ratings as ratings in which learners were not specifically asked about their mental effort but for example their study efforts (e.g., Koriat, 2018). We coded "other" if for example participants were asked how tiring an exercise was (e.g., Kirk-Johnson et al., 2019). For the subgroup analysis, we compared effect sizes from samples measured via mental effort measurements to samples measured by all other types of ratings.

Wording of Mental Effort Judgments. We coded the wording of the mental effort measurement. The majority of measurements used active wording (k = 166).

We coded the wording as active if the formulation would suggest that the learner had agency over his effort expenditure (Koriat et al., 2014), such as "investing" or "putting". If the authors mentioned having used the Paas-scale from 1992, this was coded as active as the Paas-scale uses the formulation "invest". Passive (k = 42) would be words that indicate that the learner did not have agency but that the task requirements were guiding the effort expenditure (Koriat et al., 2014), such as "requiring" or "costing". For the remaining measures (k = 28), the wording was not specified. For the subgroup analysis, we compared effect sizes from samples measured with active wording compared to samples measured via passive or not specified wording.

Reference of Mental Effort Judgments. We coded to which level the mental effort rating referred. The majority of the effort judgments referred to an item (k = 146), meaning that the judgments were made for different items of a task. In 90 cases, the judgments were made on a global task level (k = 90).

Types of Monitoring Judgments. Based on the authors' categorization, we coded what kind of monitoring judgments were measured. The majority of studies used judgments of learning (k = 169), followed by confidence ratings (k = 46), and other types of judgments (k = 21), such as a learner's self-assessment (e.g., Baars & Wijnia, 2018). For the subgroup analysis, we compared effect sizes measured with JOLs compared to all other types of judgments.

Timing of Monitoring Judgments. We coded the timing of monitoring judgments. We coded judgments as prospective if the judgments of learning/performance occurred prior to performing the task that was judged (i.e., predictions; k = 157). We coded judgments as concurrent if judgments were made during the task that was judged (k = 76). We coded judgments as retrospective if judgments were made after completing the entire task that was judged (k = 3). For the subgroup analysis, we compared effect sizes measured with prospective judgments compared to concurrent judgments.

Reference of Monitoring Judgments. We coded to which level the monitoring judgment referred. The majority of the monitoring judgments referred to an item (k = 125), meaning that the judgments were made for different items of a task. In 111 cases, the judgments were made on a global task level (k = 111).

Type of Task. We coded the type of tasks participants had to work on. The majority of tasks were problem-solving tasks (k = 98), followed by other types of tasks (k = 55), text comprehension tasks (k = 45), image learning tasks (k = 30), and word learning tasks (k = 8). For the subgroup analysis, we compared effect sizes measured during problem-solving tasks compared to effect sizes measured during all other types of tasks.

Task Difficulty. Based on the authors' categorization, we coded the task difficulty. In the majority of cases, task difficulty was not specified (k = 157), in 56 cases the authors indicated using varying levels of difficulty (k = 56), followed by difficult tasks (k = 15), other levels of difficulty (k = 5), or easy tasks (k = 3). For the subgroup analysis, we compared effect sizes measured during tasks with not specified task difficulty,

compared to effect sizes measured during all other types of task difficulty.

Goal-Driven Manipulations. We coded to what extent goal-driven manipulations were used. The majority of cases did not include goal-driven manipulations (k = 220). In 16 cases, a goal-driven manipulation was present (k = 16). Examples of goal-driven manipulations were, whether there was a time limit/time pressure to conduct a task (e.g., Koriat, 2018), if researchers tried to promote learner's sense of agency (e.g., Koriat et al., 2014), or tried to promote learner's effort investment (via, for example, instructions; e.g., Onan et al., 2023).

Analytic Approach

We used a meta-analytic structural equation model (MASEM) to analyze our data. All analyses were performed using RStudio (Version 4.2.1; RStudio Team, 2022). As articles reported multiple studies with multiple samples, our data had a nested structure. We considered this dependency by following the WPL approach (Stolwijk et al., 2022; Van den Noortgate et al., 2013; Wilson et al., 2016). Using this approach, we first estimated the synthesized correlation matrix using a three-level hierarchical model. First, to account for dependency amongst effect sizes within each article, we included the article number in our random effects structure. This level assumes that scores within one article can be more similar than scores from other articles. Second, to account for a dependency amongst scores within the same sample, we included the sample ID. This level assumes that scores within one sample are more similar than scores across samples. Third, we added a unique identifier of each task within each independent sample to our random-effects structure. Due to the limited number of articles that reported effect sizes from multiple studies (k = 8), we did not specify this as an additional level. Thus, our random-effects structure was specified as "~ 1 | ArticleID/SampleID/MeasureID."

Similar to Stolwijk et al. (2022), we used a random-effects-no-intercept model with maximum likelihood estimation to compute the unadjusted synthesized correlation coefficients for the pooled correlation matrix using the metafor package (Version 4.2.0; Viechtbauer, 2010). We then used this pooled correlation matrix as well as the asymptotic covariance matrix for the Stage 2 analysis.

Based on our hypothesized model, we first specified a full mediation model with mental effort as predictor, monitoring as mediator, and learning outcomes as outcome variable. We then compared the model fit to a partial mediation model. We assessed model fit by comparing the models using the chi-squared difference test ($\Delta\chi 2$), considering a significance level of $\alpha = .05$ to indicate a substantial difference between the two models. Furthermore, we used additional fit indices like RMSEA and CFI. RMSEA values and their 95% confidence intervals were interpreted following the benchmarks for acceptable (RMSEA ≤ .08) and good (RMSEA ≤ .05) model fit by Hu and Bentler (1998). CFI values exceeding .95 suggest a reasonable fit (Schermelleh-Engel et al., 2003). We conducted our moderator analysis, by using the subgroup analysis approach (Jak & Cheung, 2018) to investigate for each moderator separate-

ly whether the parameter estimates differed per subgroup. We did the Stage 2 analysis and the moderator analyses via the metaSEM package (Version 1.3.0; Cheung, 2015).

We interpreted the magnitude of our effect sizes following the rule of thumb by Keith (2015) who established this based on their expertise of effects on learning outcomes. For the direct effects, we considered betas above .05 as small, betas above .10 as moderate, and betas above .25 as large. We interpreted the size of indirect effects by considering that indirect effects are the product of two small, moderate, or large effects. This consideration leads to values of .052= .003 (small), .102= .01 (moderate), and .252= .063 (large) for interpreting the magnitude of the indirect effects.

Deviations from Pre-Registration

We initially planned to use a one-stage meta-analytic structural equation (OMASEM) mediation model (Jak et al., 2021) to test the mediation path model. To our knowledge, the OMASEM approach does not allow the inclusion of multiple effect sizes per sample since we can then no longer assume independence between effect sizes. Therefore, in cases of multiple effect sizes of the same sample (i.e., within-subjects design), we planned on aggregating the effect sizes to a mean effect size. In case of separate effect sizes for non-overlapping subsamples (i.e., between-subjects design), we planned to treat them as separate studies in the analysis and thus ignore dependency. However, Stolwijk et al. (2022) proposed a superior method to deal with dependency (i.e., the multilevel approach) which can be used by following a two-stage meta-analytic structural equation mediation model. We thus, followed that approach, which allowed us to take into account the non-overlapping subsamples.

Furthermore, we planned to analyze the moderator goal-driven manipulations. However, it turned out that, in most studies, there was no goal-driven manipulation (k = 220). Only 16 measures were taken under a goal-driven manipulation. Therefore, we decided against analyzing this moderator.

Additionally, we coded whether a regulation strategy was used in the included studies and planned to explore the relationship between mental effort, monitoring judgments, and regulation strategies. Using the same analysis approach as for our first research question, we intended to specify mental effort as the predictor, monitoring judgments as the mediator, and instead of learning outcomes, regulation behavior as outcome variable. Due to the low number of studies that measured regulation behavior (k = 12), we did not analyze this relationship or the exploratory moderator type of regulation strategy.

Results

Study Descriptives

The current sample consisted of data from 35 manuscripts, with 83 independent

samples, 236 effect sizes, and a total sample size of N = 3973. Of the studies, 97.1% reported multiple effect sizes. Most studies were conducted in Europe (k = 154), followed by Asia (k = 26), North America (k = 23), online (k = 21), and Australia (k = 12). The median age of the overall sample was Mdn = 22.32, with ages ranging from 9 to 70.8 years.

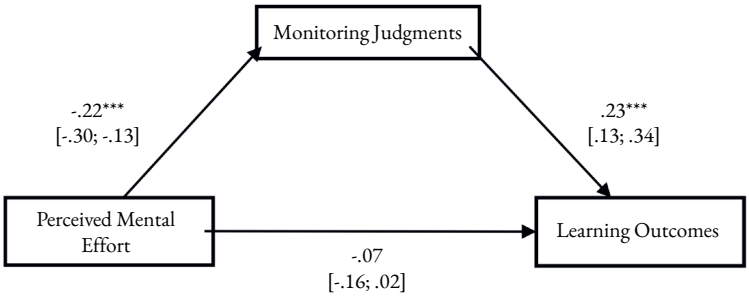
Main Analyses

To investigate our first three research questions, we specified a full mediation model as well as a partial mediation model with perceived mental effort as predictor, monitoring judgments as mediator, and learning outcomes as outcome variable. We specified the direct paths between mental effort and monitoring judgments and monitoring judgments and learning outcomes. Additionally, we specified the indirect effect from mental effort to learning outcomes via monitoring judgments. For the partial mediation model, we added the direct effect between mental effort and learning outcomes (for the differences between the models, please see Figures 1 and 2). The results of the partial mediation model are included in Figure 1. The model suggests a negative, statistically significant parameter estimate between mental effort and monitoring judgments β = -.22, 95% LBCI [-.30; -.13], a positive, statistically significant parameter estimate between monitoring judgments and learning outcomes β = .23, 95% LBCI [.13; .34], and a negative, statistically non-significant parameter estimate between mental effort and learning outcomes β = -.07, 95% LBCI [-.16; .02]. The goodness of fit indices of the model indicate that the model is saturated and overfitted and should thus be interpreted with caution, $\chi2(0) = 0$, p = .00, with a RMSEA of .00, 95% CI [.00; .00], and the CFI of 1. Due to the saturated partial mediation model, we specified a more parsimonious full mediation model, with the direct paths between mental effort and monitoring judgments and monitoring judgments and learning outcomes. Additionally, we specified the indirect effect from mental effort to learning outcomes via monitoring judgments. The $\chi2$ of the hypothesized full mediation model was statistically non-significant, $\chi2(1) = 2.57$, p = .1, so the null hypothesis of exact fit cannot be rejected. Also, the RMSEA of .01, 95% CI [.000; .051], and the CFI of .98 indicated a close approximate fit of the model.

Model comparison showed non-significant differences between the full and partial mediation model, suggesting that the saturated partial mediation model was not a significantly better fit than the more parsimonious full mediation model, and we thus continued our analysis with the full mediation model (see Figure 2). In support of Hypothesis 1, a negative parameter estimate between mental effort and monitoring judgments was found β = -.19, 95% LBCI [-.27; -.12], indicating that with each unit increase in perceived mental effort, monitoring judgments decrease by 0.19 units on average. In support of Hypothesis 2, a positive parameter estimate between monitoring judgments and learning outcomes was found β = .29, 95% LBCI [.22; .36], indicating that with each unit increase in monitoring judgments, learning outcomes increased by .29 units on average. In support of Hypothesis 3, representing the indi-

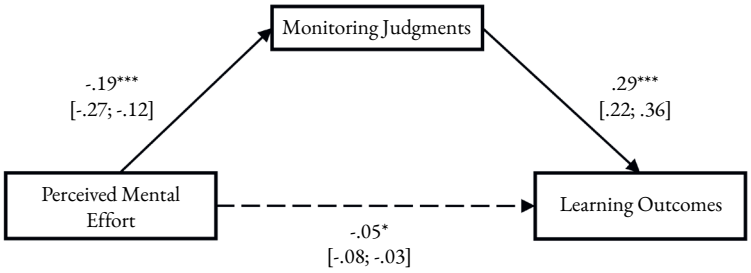
rect effect between mental effort and learning outcomes via monitoring judgments, a negative parameter estimate was found β = -.05, 95% LBCI [-.08; -.03]. This indicates that one unit increase in perceived mental effort, on average, was associated with a .05 unit decrease in learning outcomes due to the negative effect of perceived mental effort on monitoring judgments, which, in turn, positively related to learners' learning outcomes. Based on the 95% likelihood-based confidence intervals, which did not include 0 for all three coefficients, we concluded that all effects were significantly different from 0 with $p < .05$.

Figure 1. Partial Mediation Model



Note: The figure presents the partial mediation model, which was not indicated as having a significantly better fit compared to the more parsimonious full mediation model. The standardized regression coefficients of the direct effects specified in the model are indicated.

Figure 2. Full Mediation Model



Note: The figure presents the full mediation model, which was indicated as having good fit indices while not being overfitted. The standardized regression coefficients of the direct effects specified in the model are indicated. Additionally, the indirect effect between mental effort and learning outcomes was specified in the full mediation model and is represented with the dashed arrow. All three paths were significant at $p < .05$.

Moderator Analysis

We conducted various moderator analyses using subgroup analysis with education (higher and postgraduate education vs other types of education), mental effort meas-

urement (mental effort ratings vs other types of ratings), mental effort wording (active wordings vs other wordings), effort reference (item-by-item level vs global task level), type of monitoring (JOL vs other types of monitoring), monitoring timing (prospective vs concurrent), type of task (problem-solving vs other types of tasks), and task difficulty (not specified vs other difficulty levels) as moderators. We used the full mediation model and investigated whether the subgroup analysis would reveal significant differences in regression coefficients across groups.

Our subgroup analysis revealed no significant differences for any of the moderators at $p < .05$. The regression coefficients and their corresponding 95% likelihood-based confidence intervals from the full mediation model ran per subgroup can be found in Table 2.

Table 2. Results Moderator Analysis

Moderator	Subgroup	Relationship	β	95% CI
Education	Higher / Post Education	Effort-Monitoring	-.19	[-.28; -.10]
		Monitoring-Learning outcome	.29	[.21; .37]
		Effort-Learning outcome (Indirect)	-.05	[-.08; -.03]
	Other Education	Effort-Monitoring	-.23	[-.31; -.15]
		Monitoring-Learning outcome	.26	[.17; .35]
		Effort-Learning outcome (indirect)	-.06	[-.09; -.03]
Effort Measurement	Mental effort ratings	Effort-Monitoring	-.19	[-.28; -.11]
		Monitoring-Learning outcome	.29	[.21; .37]
		Effort-Learning outcome (Indirect)	-.05	[-.08; -.03]
	Other effort ratings	Effort-Monitoring	-.19	[-.34; -.04]
		Monitoring-Learning outcome	.29	[.16; .43]
		Effort-Learning outcome (indirect)	-.05	[-.10; -.01]
Effort Wording	Active	Effort-Monitoring	-.18	[-.28; -.08]
		Monitoring-Learning outcome	.30	[.21; .39]
		Effort-Learning outcome (Indirect)	-.05	[-.08; -.03]
	Other wording	Effort-Monitoring	-.19	[-.31; -.07]
		Monitoring-Learning outcome	.29	[.19; .40]
		Effort-Learning outcome (indirect)	-.05	[-0.09; -.02]
Effort Reference	Item-by-item	Effort-Monitoring	-.20	[-.29; -.11]
		Monitoring-Learning outcome	.29	[.20; .38]
		Effort-Learning outcome (Indirect)	-.06	[-.08; -.03]
	Global task	Effort-Monitoring	-.18	[-.31; -.05]
		Monitoring-Learning outcome	.30	[.20; .41]
		Effort-Learning outcome (indirect)	-.05	[-.09; -.02]
Monitoring Type	JOL	Effort-Monitoring	-.19	[-.28; -.09]
		Monitoring-Learning outcome	.30	[.22; .38]
		Effort-Learning outcome (Indirect)	-.05	[-.08; -.03]
	Other types	Effort-Monitoring	-.22	[-.31; -.12]
		Monitoring-Learning outcome	.28	[.19; .37]
		Effort-Learning outcome (indirect)	-.06	[-.09; -.03]

Moderator	Subgroup	Relationship	β	95% CI
Monitoring Timing	Prospective	Effort-Monitoring	-.19	[-.29; -.08]
		Monitoring-Learning outcome	.30	[.21; .39]
		Effort-Learning outcome (Indirect)	-.05	[-.08; -.03]
	Concurrent	Effort-Monitoring	-.22	[-.32; -.12]
		Monitoring-Learning outcome	.27	[.18; .37]
		Effort-Learning outcome (indirect)	-.06	[-.09; -.03]
Monitoring Reference	Item-by-item	Effort-Monitoring	-.21	[-.30; -.13]
		Monitoring-Learning outcome	.28	[.19; .37]
		Effort-Learning outcome (Indirect)	-.06	[-.09; -.03]
	Global task	Effort-Monitoring	-.17	[-.28; -.05]
		Monitoring-Learning outcome	.31	[.21; .41]
		Effort-Learning outcome (indirect)	-.05	[-.08; -.02]
Task Type	Problem-solving	Effort-Monitoring	-.18	[-.28; -.08]
		Monitoring-Learning outcome	.30	[.22; .39]
		Effort-Learning outcome (Indirect)	-.05	[-.08; -.02]
	Other task types	Effort-Monitoring	-.19	[-.29; -.10]
		Monitoring-Learning outcome	.29	[.21; .38]
		Effort-Learning outcome (indirect)	-.05	[-.08; -.03]
Task difficulty	Not specified	Effort-Monitoring	-.20	[-.29; -.10]
		Monitoring-Learning outcome	.29	[.21; .37]
		Effort-Learning outcome (Indirect)	-.05	[-.08; -.03]
	Other levels difficulty	Effort-Monitoring	-.19	[-.32; -.06]
		Monitoring-Learning outcome	.29	[.17; .42]
		Effort-Learning outcome (indirect)	-.05	[-.10; -.02]

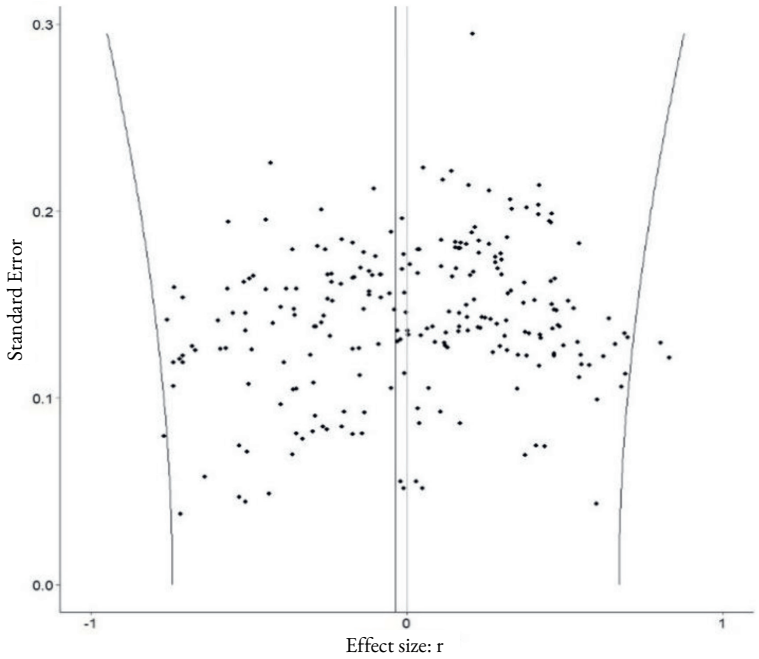
Note: In the table, the standardized regression coefficient and their corresponding 95% likelihood-based confidence interval are displayed. These coefficients were based on the full mediation model that was run for each of the subgroups separately and then compared for statistically significant differences in their effects.

Publication Bias Analysis

We evaluated publication bias using a three-level funnel plot of all effect sizes (Fernández-Castilla et al., 2020). The funnel plot below (Figure 3) displays the collected effect sizes against their measurement precision, in this case, the standard error. Visual inspections of the plot reveal an asymmetric shape as there are for example little studies with a larger, negative effect size and larger standard error, which indicates that there could potentially be selection or publication bias. We investigated this further by conducting a p-curve analysis using the p-curve app (Version 4.06; Simonsohn et al., 2014). Via this analysis, it is possible to investigate the likelihood of the findings underlying a true effect or if they are a result of selective reporting. The p-curve represents the distribution of statistically significant p-values ($p < .05$). Right-skewed p-curves suggest that included studies contain more low (e.g., .01s) than high (e.g., .04s) significant p-values and thus provide diagnostic evidence of the presence of evidential value for a true effect. The results of the p-curve analysis showed that the dis-

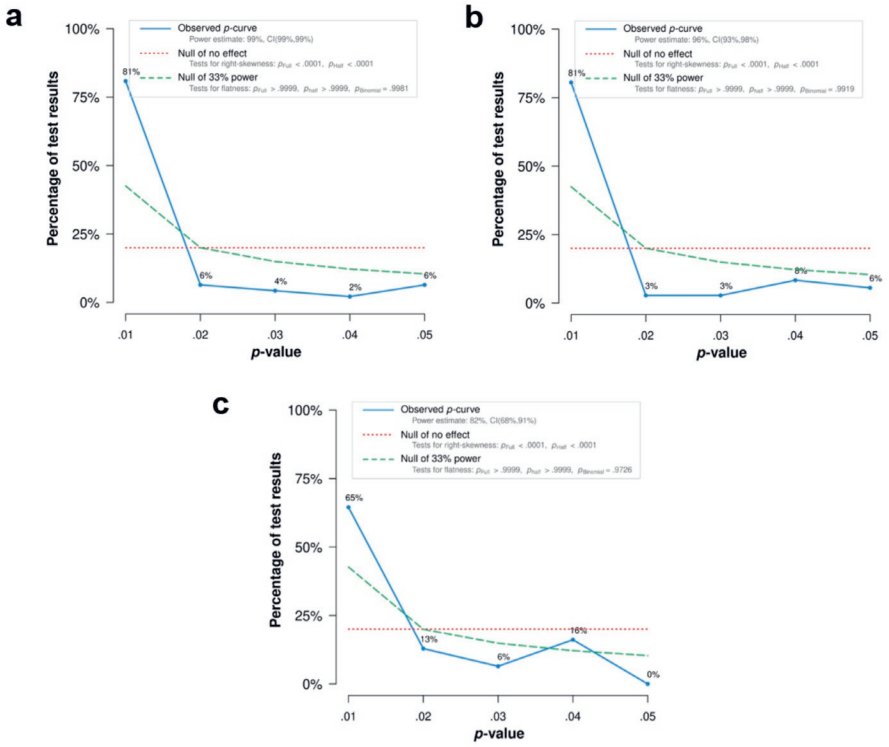
tributions of effects underlying the correlations between perceived mental effort, monitoring judgments, and learning outcomes were right-skewed (Figure 4a; perceived mental effort and monitoring judgements, binomial test $p < .001$, continuous test: $Z = -19.31$, $p < .001$; Figure 4b, monitoring judgements and learning outcomes, binomial test $p < .001$, continuous test: $Z = -13.74$, $p < .001$; Figure 4c, perceived mental effort and learning outcomes, binomial test $p < .001$, continuous test: $Z = -8.53$, $p < .001$). The p-curves thus indicate evidential value underlying the relationships.

Figure 3. Funnel Plot of all Effect Sizes



Note. The figure shows a funnel plot displaying the collected effect sizes against their standard error.

Figure 4. P-Curve Analysis of the Effect Sizes per Relationship



Note. P-curve analysis of studies on the relationship between mental effort, monitoring judgments, and learning outcomes presenting the distribution of significant p-values. 4 a) Analysis of the correlations between mental effort and monitoring judgments. The observed p-curve includes 47 statistically significant ($p < .05$) results, of which 41 are $p < .025$. There were 36 additional results entered but excluded from the p-curve because they were $p > .05$. 4b) Analysis of the correlations between monitoring judgments and learning outcomes. The observed p-curve includes 36 statistically significant ($p < .05$) results, of which 31 are $p < .025$. There were 41 additional results entered but excluded from the p-curve because they were $p > .05$. 4c) Analysis of the correlations between mental effort and learning outcomes. The observed p-curve includes 31 statistically significant ($p < .05$) results, of which 26 are $p < .025$. There were 45 additional results entered but excluded from the p-curve because they were $p > .05$.

Discussion

In the current study, we aimed to investigate the relationship between perceived mental effort, monitoring judgments, and learning outcomes using a meta-analytic approach. Based on our model comparison, the more parsimonious full mediation model compared to the partial mediation model indicated good fit indices while not being overfitted. Thus, we based our results on the full mediation model. In line with Hypothesis 1, we found a moderate, negative association between perceived men-

tal effort and monitoring judgments (β = -.19). This indicates that if a learner judges their perceived mental effort to be high, they will judge their perceived learning (reflected by their monitoring judgment) as low. This indicates that perceived mental effort is potentially used as a cue and aligns with earlier research (Baars et al., 2020). In line with Hypothesis 2, we found a large, positive relationship between monitoring judgments and learning outcomes (β = .29). This indicates that if a learner judges their perceived learning (reflected by their monitoring judgment) as high, their learning outcomes during the task would also be higher. Similarly to Blissett et al. (2018), we would still interpret this as low to moderate accuracy when monitoring one's learning due to the beta coefficient. However, this interpretation of magnitude should be regarded with caution as relative metacomprehensive accuracy is typically judged via the Gamma or Pearson correlation coefficients (for a recent meta-analysis on relative metacomprehension accuracy, see Prinz et al., 2020a). In line with Hypothesis 3, we found a significant negative, moderate-sized indirect association between perceived mental effort and learning outcomes (β = -.05), which was mediated by monitoring judgments. This suggests that when learners perceive higher levels of mental effort, their learning outcomes tend to decrease as mediated by monitoring judgments, indicating the important role of monitoring judgments in explaining the relationship between perceived mental effort and learning outcomes. These findings imply that learners use their perceptions of invested mental effort as a cue when monitoring learning, while the significant indirect negative effect between effort and learning outcomes indicates that mental effort might be indirectly related to actual learning outcomes. More specifically, the negative indirect effect seems to indicate that when learners experience high mental effort, this is associated with lower feelings of learning or confidence, which in turn relates to actual lower learning. When learners experience lower mental effort, this is associated with higher feelings of learning or confidence, which in turn relates to higher actual learning. This suggests that when learners perceive high mental effort, they seem to score lower on the learning outcomes. In line with the cue-utilization perspective, our findings suggest that learners judged their learning outcomes relatively accurately (due to the positive direct effect between monitoring judgments and learning outcomes) to be lower (due to the negative direct effect between perceived mental effort and monitoring judgment) when they experienced high mental effort.

The lack of a statistically significant direct relationship between perceived mental effort and learning outcomes could be explained by cognitive load theory (Sweller et al., 1998, 2019). As introduced earlier, the relationship between mental effort and learning outcomes could be positive when task requirements meet the learner's working memory capacity and the cognitive effort necessary for processing and integrating information is directly relevant to learning. When the mental effort required for a learning task exceeds this capacity, learning is hampered and the relationship between mental effort and learning outcomes becomes negative. In addition, it might be that in some instances learners' perceived high mental effort is due to factors such as sub-

optimal task design, a distracting environment, less effective strategies, or incorrect strategy utilization, which are not conducive to effective learning. When learners experience high mental effort due to such non-learning conducive factors (i.e., high extraneous load; Paas & Van Merriënboer, 1994), we would anticipate the relationship between mental effort and learning outcomes to be different compared to instances in which task design is optimal, the environment is distraction-free, and learners employ correct learning/problem-solving strategies. Future research could investigate to what extent task design and strategy use play a role in the relationships between mental effort, monitoring judgments, and learning outcomes.

Another factor, which could potentially explain the statistically non-significant direct relationship between mental effort and learning outcomes, is that the studies included in this meta-analysis might have been too heterogeneous in their approximation of mental effort and/or load. Although we did not find evidence for this in our subgroup analysis, it could be that the use of different self-report questions and formulations hereof might have caused too much noise to detect a significant relation or by measuring extraneous and germane load at the same time and combining them to indicate load (e.g., Schleinschok et al., 2017).

When investigating the direct relationships between perceived mental effort, certainty as the monitoring judgment, and learning outcomes, Blissett and colleagues (2018) found a significant negative relationship between mental effort and monitoring ($\beta = -.37$) and a significant positive relationship between monitoring and learning outcomes ($\beta = .34$). The results from our study extend these findings by discovering similar results across different settings, tasks, and populations. Additionally, they found a significant negative relationship between mental effort and learning outcomes ($\beta = -.17$) which they interpreted as mental effort being diagnostic due to its predictive value for learning outcomes. Our model comparison showed non-significant differences between the full and partial mediation model, suggesting that the saturated partial mediation model with a direct effect from mental effort to learning outcomes was not a significantly better fit than the more parsimonious full mediation model. Extending the findings from Blissett and colleagues (2018), our findings suggest evidence for an indirect rather than a direct effect between mental effort and learning outcomes, mediated by monitoring judgments.

Our data seem to support the idea that effort is used as a cue for monitoring even though it is not directly related to learning outcomes, highlighting the importance of metacognition during learners' self-regulated learning. As perceived mental effort seems to be used as a cue, it is important to teach students how to interpret their mental effort experience correctly and use it adequately when monitoring their learning. Our findings show that learners tend to interpret it as negatively related to learning when in reality this is not necessarily the case. Additionally, the mediation pathway between mental effort and learning outcomes through monitoring indicates a potentially important role that monitoring has in linking perceived mental effort to actual learning outcomes. Incorporating and further exploring this mediation mecha-

nism into self-regulated learning models could further enhance our understanding of the on-task experiences learners have and how these relate to their actual learning outcomes.

To counteract learners' low metacognitive skills, instructional approaches that support learners in aligning their perceived effort and perceptions of learning with their actual learning, are necessary. Generative strategies such as generating keywords, summaries, or diagrams when learners are required to read a text, have been suggested to facilitate learners' monitoring accuracy by providing learners with more salient access to more diagnostic cues (Prinz et al., 2020b). Educators could for example try to integrate such strategies to facilitate learners' calibrations of their perceived learning. Furthermore, providing learners with feedback on their actual learning outcomes could help them to gain a deeper understanding of their actual learning and the corresponding on-task experiences (De Bruin et al., 2023).

Alternatively, to increase monitoring accuracy, it might be important to refrain from asking learners to rate their mental effort, to reduce the use of effort as a cue for monitoring. While there is unpublished data by Raaijmakers et al., (2023), which indicates that the order of mental effort and monitoring judgment administration does not influence learners' ratings, it might be that the specific combination of perceived mental effort ratings and monitoring judgments could cause changes in monitoring judgments compared to situations in which only monitoring judgments are administered.

Hoch and colleagues (2023) who examined the predictive value of mental effort, task difficulty, and confidence appraisals for performance, found that compared to effort appraisals, confidence, and difficulty appraisals demonstrated stronger associations with performance. They concluded that mental effort appraisals reflect fluency and might thus not serve as reliable predictors of actual performance and instead are misleading (Hoch et al., 2023). These findings suggest that monitoring judgments instead of mental effort might be more reliable predictors of learning success and could thus potentially serve as a more reliable cue when for example taking a regulatory decision.

However, there are also situations during which effort is diagnostic of learning outcomes, but this diagnosticity could still be misleading. For example, in the case of desirable difficulties (i.e., learning conditions that are experienced as effortful while also enhancing learning and long-term retention; Bjork & Bjork, 2011) learners often misinterpret this higher mental effort as a cue for low learning which biases learners to lower judgments of their learning and to choose learning strategies that require less mental effort (Hui et al., 2022; Kirk-Johnson et al., 2019; Onan et al., 2022). Also, when using desirable difficulties, initial learning can be lower compared to other learning strategies. For example, when using retrieval practice compared to re-study, the beneficial effects can become evident only after a few days (Karpicke & Roediger, 2008; Nunes & Karpicke, 2015). This means that immediate learning outcomes can sometimes be lower while effort is higher compared to an ineffective learning strate-

gy. Even though immediate perceptions of effort during the learning task would not be diagnostic in this case, it is important to consider potential delayed learning effects as the cue diagnosticity of mental effort may become apparent after a delay. Learners might benefit from interventions that address this paradox and thus be able to regulate their learning accordingly (De Bruin et al., 2023). Future studies should investigate whether or not mental effort is a diagnostic cue for delayed compared to immediate learning outcomes. This could also be meaningful in order to gain a better understanding of how mental effort and monitoring relate to learning outcomes. In our analysis, we considered the relationships between mental effort, monitoring judgments, and immediate learning outcomes. Immediate learning outcomes, however, might not be the best approximation for long-term learning, thus limiting the interpretation of our results. More specifically, the fact that monitoring judgments are positively associated with immediate learning outcomes does not necessarily mean that they are also positively related to long-term learning. The studies included in this meta-analysis commonly measured learning outcomes immediately after a learning task or after a short delay. Furthermore, if transfer was included, this was usually a near-transfer task. Due to the lack of temporal changes and far-transfer tasks captured in the included studies, we cannot differentiate between performance and learning as suggested by Soderstom and Bjork (2015) as we do not know whether the changes in behavior/knowledge were permanent. Future research should investigate to what extent perceived mental effort and monitoring judgments relate to long-term learning.

Surprisingly, our moderator analysis revealed no significant differences across subgroups. More specifically, the moderators education, mental effort measurement, mental effort wording, effort reference, type of monitoring, monitoring timing, monitoring reference, and type of task or task difficulty did not significantly moderate the relationships between mental effort, monitoring judgments, and learning outcomes. This finding contrasts with previous findings such as the meta-analysis by Baars and colleagues (2020), who found timing of monitoring judgment, type of task, and goal-driven manipulations significantly moderated the relationship between mental effort and monitoring. While we were not able to assess the moderator goal-driven manipulations due to the small number of goal-driven manipulations in our sample, we did not find a significant difference in the magnitude of effect sizes for timing of monitoring judgment or type of task.

A potential reason for these different findings might be the statistical analysis approach used. Using a multilevel meta-analytic structural equation model, we conducted a subgroup analysis and thus investigated whether the effect sizes in the full mediation model were statistically different amongst samples from two different subgroups. We did not test the moderating influence of the variables on the separate paths. To our knowledge, using a multilevel meta-analytic structural equation model with subgroup analysis is currently the best way to examine the influence of moderating variables in a two-stage model (Jak & Cheung, 2018). Furthermore, another potential reason for this incongruence in findings compared to earlier work could be the

limited number of studies we were able to include in our analysis or a lack of variability within our moderators. Additionally, Baars and colleagues (2020) did not focus on perceived mental effort as measured by self-report items only but also took (mental) effort indicators such as response time or time on task into account. This broader perspective on (mental) effort might have caused the difference in results. In the present study, we focused on perceived mental effort as a more subjective representation of effort compared to a more objective operationalization, via for example time on task, for two reasons. During self-regulated learning, learners often need to regulate their effort investment. In order to do so, they need to monitor their effort. As learners usually do not have direct access to the mental effort they invested during a task, they infer the amount of mental effort based on subjective experiences of effort (De Bruin et al., 2023). Therefore, in the context of self-regulated learning, perceived mental effort seemed a more appropriate operationalization compared to a more objective one. A second reason was to avoid ambiguity between learning outcomes and effort measures. While for example time on task is sometimes operationalized as an indication of mental effort, it is also often used as a learning outcome measure. To avoid this ambiguity, we focused on perceived mental effort only. Future studies could investigate this further by testing whether the current findings extend to studies employing other operationalization of (mental) effort such as study time. Such an approach might also be interesting in light of the previously raised point that the specific combination of perceived mental effort ratings and monitoring judgments could potentially cause changes in monitoring judgments compared to situations in which only monitoring judgments are administered. However, unpublished data indicates that the order of administration seems to not influence mental effort ratings or monitoring judgments (Raaijmakers et al., 2023).

Limitations and Future Studies

The current study has various limitations, which should be taken into consideration when interpreting these findings. First, the effect sizes used in our study were purely correlational, thus limiting our ability to establish causal relationships. In line with the cue-utilization framework (Koriat, 1997), we theorized directional paths from mental effort to monitoring, from monitoring to learning outcomes, and from mental effort to learning outcomes. While our study contributes to an increased understanding of the associations across diverse studies, the observed correlations do not confirm the directionality or causality of these relationships. For example, we cannot exclude the fact that the relationships between some of the variables are reversed. More specifically, it might be the case, that in some instances perceived mental effort and monitoring judgments are influenced by learning outcomes. Raaijmakers and colleagues (2017) found that performance feedback influenced learners' perceptions of their invested effort. While we cannot exclude this reversed directionality, the majority of studies included in this meta-analysis did not provide learners with access to

their actual learning outcomes, and commonly mental effort judgments and monitoring judgments were asked prior to the learning outcome measure. In order to gain more insight into the causal relationships between mental effort, monitoring, and learning outcomes, future research could manipulate learners' experience of their perceived mental effort or their monitoring which would allow for causal inference and would thus be essential in validating the directionality of the proposed relationships within the cue-utilization framework. Additionally, it is important to acknowledge the current lack of comprehensive understanding regarding optimal strategies to assist learners in effectively monitoring and regulating their learning. We argue that accurate monitoring is a requirement for effective self-regulated learning. However, research suggests, that accurate monitoring does not necessarily mean that learners will actually engage in (beneficial) regulation. For example, prompting learners to monitor their understanding or informing them about the dangers of inaccurate monitoring does not necessarily lead to improved learning outcomes (Berthold et al., 2007; Nueckles et al., 2020; Roelle et al., 2017). This suggests that even if learners are able to accurately monitor their learning, they will not necessarily engage in effective self-regulation due to for example the additional mental effort that is required but not available to regulate effectively (De Bruin et al., 2023).

Furthermore, due to the correlational nature of the data, it might be the case that an underlying third variable such as motivation influences the associations between mental effort, monitoring judgments, and learning outcomes. Research has shown that motivational profiles were related to monitoring accuracy and learning outcomes after self-regulated learning skills training (Baars & Wijnia, 2018; Wijnia & Baars, 2021). Specifically, results showed that learners with higher-quality motivation obtained better scores on monitoring accuracy and problem-solving tasks after the intervention. Results further suggested that participants with lower-quality motivation perceived the learning task as more effortful than students with higher-quality motivation. Therefore, individual differences in learners' motivation could potentially serve as a third variable influencing the observed correlations. Depending on learners' motivation, they might experience increased mental effort and more accurate monitoring of their learning processes. Additionally, motivational profiles might independently contribute to enhance their learning outcomes. As we did not have access to learners' motivation, we cannot rule out the possibility that the observed associations may be confounded by, for example, learners' motivation. Future research could incorporate measures of motivation or manipulate motivation for a more nuanced understanding of the relationships between mental effort, monitoring, and actual learning outcomes. Moreover, in order to gain more insight into the causal relationships between mental effort, monitoring, and learning outcomes, future research could manipulate learners' experience of their perceived mental effort or their monitoring which would allow for causal inference and would thus be essential in validating the directionality of the proposed relationships within the cue-utilization framework.

Second, we included a relatively small number of studies in our analysis. While there is no common cut-off score of minimum number of studies necessary to apply meta-analytic structural equation modeling, it is suggested to include a sufficient number of studies to ensure the reliability and generalizability of the meta-analytic findings. A small number of studies might limit the statistical power and precision of the analysis, making it challenging to draw meaningful conclusions. Additionally, the studies we selected for our meta-analysis stem from a particular intersection of research into metacognition and cognitive load theory. It is possible that this intersection excluded certain research lines or paradigms, where, e.g., measures of effort are not typically used. The conclusions drawn regarding the relationships of interest are situated within these frameworks and while providing valuable insights within this theoretical context, their generalizability to broader educational settings or other fields of research might therefore be limited. Future studies should investigate the relationships further and consolidate our findings.

Third, the role of the moderators that were tested in the current study needs further investigation. We were not able to replicate previous meta-analytic findings, which identify moderating effects of certain types of tasks and timing of judgments. Potential reasons for this include the lack of variability in our moderators or the limited sample size. Future research is necessary to disentangle the effects moderators might have on the relationships between mental effort, monitoring judgments, and learning outcomes.

Fourth, we have restricted the publication period of studies eligible for our meta-analysis and only included studies published in the year 2000 or thereafter. We decided to do so to maintain the contemporary relevance of results, to increase the likelihood of homogeneity in the studies' employed methodology and technology, and because the influential cue-utilization framework (Koriat, 1997) underlying the majority of relevant studies was published in 1997, which is why we did not expect many relevant studies before 2000. However, in restricting the publication period we might have biased our selected sample and missed influential studies published before the year 2000.

Conclusion

In the current study, we investigated the association between mental effort, monitoring, and learning outcomes using a meta-analytic approach. The results indicate a negative association between mental effort and monitoring judgments, a positive association between monitoring judgments and learning outcomes, and a significant indirect association between mental effort and learning outcomes mediated by monitoring judgments. Surprisingly, our subgroup analysis did not reveal any significant differences across moderators. These findings suggest that mental effort is used as a cue for monitoring judgments and is only indirectly related to immediate learning outcomes via monitoring judgments. We did not find evidence that these relationships were influenced by certain task or learner characteristics.

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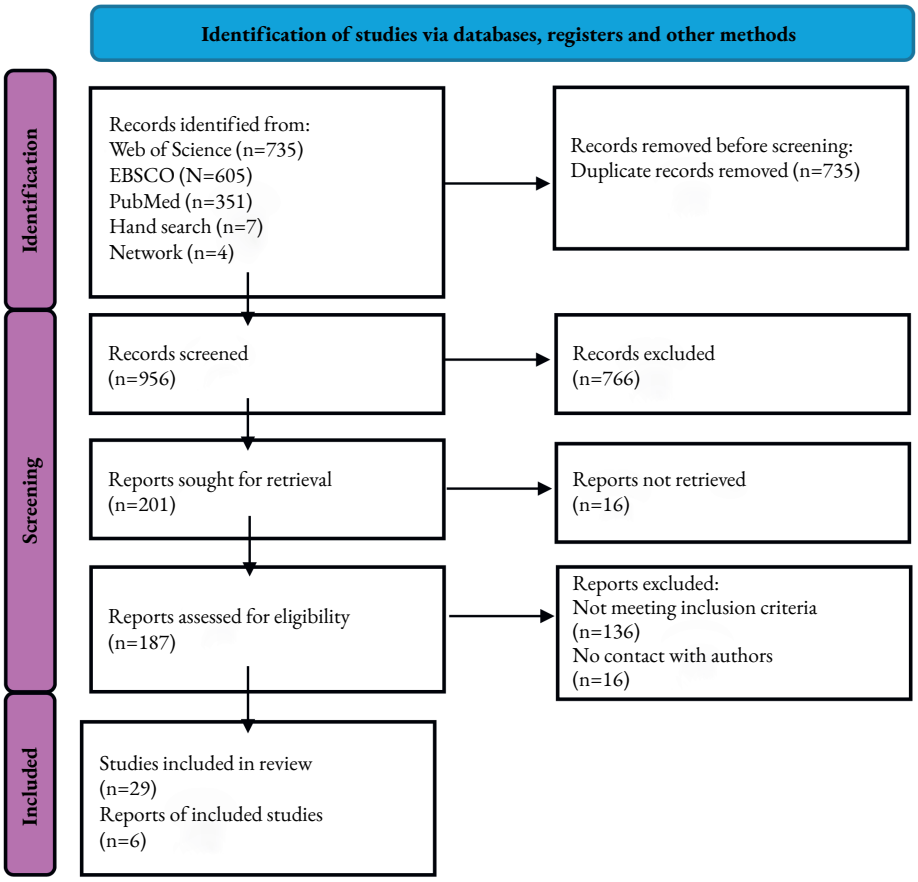
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Appendix A. Supplementary Material: Adapted PRISMA 2020 flow diagram



Adapted From: Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., ... Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ, n71. https://doi.org/10.1136/bmj.n71. A template of this diagram was retrieved from http://www.prisma-statement.org/PRISMAStatement/FlowDiagram

Chapter 3

The Challenge of Change: Understanding the Role of Habits in University Students' Self-Regulated Learning

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Abstract

Study habits drive a large portion of how university students study. Some of these habits are not effective in fostering academic achievement. To support students in breaking old, ineffective habits and forming new, effective study habits, an in-depth understanding of what students' study habits look like and how they are both formed and broken is needed. Therefore, in this study, we explored these aspects among first-year university students in six focus group discussions (N = 29). Using a thematic analysis approach we clustered the data in five themes: Goals Matter, Balancing Perceived Efficiency and Effectiveness when Studying, Navigating Student Life: from Structured Routines to Self-Regulation Challenges, the Quest for Effective Habits with Trying to Break Free From the Screen as subtheme, and the Motivation Roller Coaster. Findings suggest that students had different study habits depending on their goals. Students had quite accurate metacognitive knowledge about effective learning strategies for long-term learning, but often used other learning strategies they deemed most efficient in reaching their goals. Students indicated intentions to change, but did not prioritize change as their current habits enabled them to pass exams and change was not perceived as adding value. Fluctuations in motivation and transitioning to a self-regulated life hampered students' intentions to form new and break old habits. Next to insights into factors affecting students' behavioral change intentions, the findings suggest the importance of aligning assessment methods with life-long learning and supporting students in their long-term academic goal-setting to prioritize study habits which target lasting learning to optimally foster their self-regulated learning.

Keywords: habits, desirable difficulties, self-regulated learning, behavioral change, higher education

In higher education, students are required to plan, monitor, and execute their learning autonomously (Dresel et al., 2015; Zimmerman, 1986). Therefore, effective self-regulated learning (SRL), facilitated by the use of effective learning strategies, is essential for students' academic achievement and lifelong learning (e.g., Dunlosky et al., 2013). However, many students struggle to use effective learning strategies optimal for long-term learning, such as practice testing, and often rely on passive strategies such as re-reading (Morehead et al., 2016; Rea et al., 2022). While training programs are successful in increasing students' knowledge regarding these effective learning strategies, many students struggle to sustainably change their behavior and apply these learning strategies (Biwer et al., 2020; Foerst et al., 2017; Rea et al., 2022). This gap between students' knowledge and behavior is partially due to students' strong habits of using ineffective study strategies (Blasiman et al., 2017; Rea et al., 2022). However, so far, this gap between students' knowledge and behavior and their study habits remained largely unexplored. To explore the gap between students' knowledge and behavior further, we deem it essential to first gain a thorough understanding of students' current study habits, how they usually form new, and break old habits.

Using a qualitative approach, we add to the current field of research by targeting an in-depth exploration of students' study habits, which is currently lacking. Insight into these are essential to tailor educational strategies and training to better align with students' behaviors and needs. Awareness of potential struggles students might encounter when breaking old or forming new habits provides important insights into hurdles students face when attempting to modify their study behavior and how they can be supported in achieving their goals.

Self-Regulated Learning in Higher Education

In higher education, learning is happening mostly in teacher-absent environments, which requires students to effectively self-regulate their learning (Dresel et al., 2015). However, many students struggle to self-regulate effectively. They monitor and control their learning inaccurately, which has a negative impact on their academic achievement (Hartwig & Dunlosky, 2012). One way of fostering self-regulated learning is by helping students to use learning strategies which are optimal for long-term learning (e.g., 'desirably difficult' learning strategies, Bjork & Bjork, 2011). Examples of desirably difficult learning strategies are practice testing, interleaving items of various categories, and spacing learning sessions over time (Dunlosky et al., 2013). A shared commonality of these effective strategies is that they require an active learning process with repeated memory retrieval of information (Bjork & Bjork, 2011).

While essential for self-regulated learning, students often avoid desirable difficulties or fail to use them in the long-run, even when being aware of their benefits (Biwer et al., 2020; Rea et al., 2022). One reason for not using effective learning strategies is that students often have strong habits of using surface processing strategies.

Instead of using desirable difficulties, students rely on passive learning strategies and mass their study sessions close to the exam instead of spacing the sessions over time (Blasiman et al., 2017; Dembo & Seli, 2004; Foerst et al., 2017). Often students start using these strategies in high school already (Dirkx et al., 2019).

Next to struggling to use effective learning strategies, students often face additional regulation issues during their self-study. Learners also need to employ resource-management strategies such as effort-, and motivation management to optimize learning conditions (Dresel et al., 2015) by for example planning their study sessions or asking for help if necessary. While resource-management strategies have been identified as an essential factor for academic performance (Grunschel et al., 2016; Waldeyer et al., 2019), many students struggle with time management (Basila, 2014; Thibodeaux et al., 2017) and encounter motivational problems leading to for example procrastination (Grunschel et al., 2016).

Metacognition and resource-management strategies are often indicated as important factors in self-regulated learning models (for an overview, see Panadero, 2017). However, these factors might not fully explain how students maintain recurring study behaviors over the long term (Fiorella, 2020). Instead, habits, which, once formed, are usually not guided by conscious intentions and goals, have been suggested crucial for academic behaviors that need to be repeated consistently over an extended period (Fiorella, 2020). Therefore, to foster students' self-regulated learning it has been suggested to support students in building new study habits, which for example incorporate desirable difficult learning strategies (Fiorella, 2020).

Behavioral Change and Study Habits

In the last years, interventions have been developed to enhance students' knowledge and initial use of effective learning strategies (e.g., Ariel & Karpicke, 2018; Biwer, De Bruin, et al., 2020; Broeren et al., 2021). While showing positive effects, the actual transition of this knowledge and application to students' self-study in the long-run, remains limited (Dignath & Veenman, 2020). The majority of these interventions focus more on increasing students' knowledge and less on building new habits or changing the actual study behavior consistently potentially explaining the limited application. Habits, however, are an important predictor of behavior in addition to, for example, attitudinal and control beliefs (Verhoeven et al., 2012; Verplanken, 2018), and are seen as a key factor in behavior maintenance (Rothman et al., 2009). To ultimately support students in actually applying effective learning strategies in the long-run, it is essential to first understand the factor that drives most behavior: habits (Rothman et al., 2009; Verplanken, 2018).

Habits are behaviors that reoccur in stable contexts. Once a habit forms, behavior is led by automatic, effortless actions instead of deliberate intentions (Gardner, 2015; Lally, et al., 2010). According to our conceptualization, study habits can relate to behaviors such as the usual length of a student's study session, learning strategies used,

or study timing and environment. Study habits can play an essential role in harming or helping students to achieve long-term academic goals. Irrespective of whether these habits help or hinder goal achievement, they initiate behavior automatically and effortlessly. Habits usually form when an association between a certain behavior and context is established by consistently repeating a behavior in that context (Lally & Gardner, 2013; Gardner, 2015). Due to the association, the habitual behavior is automatically and sometimes unconsciously activated (Aarts & Dijksterhuis, 2000) while alternative behaviors become less accessible (Danner et al., 2007). Often, the effort required to initiate the habitual behavior decreases over time and initiation becomes effortless (Lally et al., 2011). Even when intentions change, engagement in habitual behavior commonly persists (Adriaanse & Verhoeven, 2018).

According to the goal–habit interface model (Wood & Rünger, 2016) many habits are initiated by goal-directed behavior. Initially, before habit formation, goals drive individuals to repeat a certain action in a specific context. Once a habit is formed, the habitual behavior shifts from goal-dependent to goal-independent behavior. In this case, behaviors are enacted based on context cues and irrespective of goals (Mazar & Wood, 2018). Nevertheless, as many individuals are unaware of this habit formation process, they might misattribute their habitual behavior to goals or intentions instead of habits (Mazar & Wood, 2018; Loersch & Payne, 2011).Wood and Neal (2016) suggest various essential components for habit-based interventions that target initiation and maintenance of health behavior change. They suggest the importance of habit-forming approaches for fostering repeated engagement in healthy behaviors while also disrupting undesirable behavior by habit-breaking approaches. As main components for habit formation, they suggest frequent repetition of the desirable behavior, creating a re-occurring context and context-cues, and administering rewards randomly (Wood & Neal, 2016). To break undesirable habits, context-cue disruption, re-structuring of one's environment, and monitoring one's behavior are suggested as efficient (Wood & Neal, 2016).

While there has been quite some research showing the beneficial effects of habits in health behavior change (e.g. exercising habit, healthy eating habit), only a few studies have focused on how study habits could improve students' study behavior (e.g., Galla & Duckworth, 2015). Students' ineffective study habits such as ineffective learning strategy use (Biwer et al., 2020; Foerst et al., 2017; Rea et al., 2022), high smartphone use (Chen & Yan, 2016; Lepp et al., 2015), or poor time-management (Basila, 2014; Thibodeaux et al., 2017) seem to play a role in their study behavior and academic achievement. Breaking these ineffective habits and forming effective study habits instead by, for example incorporating more desirably difficult learning strategies, could help students to optimize their self-regulated learning and academic achievement.

In the present study, we aim to gain a better understanding of the nature of university students' study habits, how students usually form new habits, and how they (try) to break ineffective habits. We explored this using a qualitative approach via fo-

cus group discussions with first- and second- year university students. As our goal was to dive beyond surface-level observations and gain an in-depth understanding of students' experiences rather than generalizing to a larger population, a qualitative approach seemed most appropriate (Morse, 2008). Compared to a quantitative approach, a qualitative approach via focus groups or interviews offers various benefits (for a more general overview of focus group discussions in medical education, see Stalmeijer et al., 2014). First, they offer a relatively time- and cost-effective access to students' thoughts and experiences. Second, by being able to directly engage with students, it is possible to ask students for further elaboration or clarification, which would not be possible using for example questionnaires and therefore ensuring an in-depth understanding. Third, due to the flexibility of this approach and our semi-structured question guide, we were able to capture students' opinions while limiting imposing pre-existing assumptions about their study habits. Most importantly though, we anticipated that the interactions between students would be essential when discussing study habits and focus group discussions would thus allow a more diverse and multifaceted picture of students' study habits. While habitual behaviors could be unconscious, we expected that hearing other students' experiences would facilitate students' reflections of similar or dissimilar experiences. Insights from our study can help to inform potential future study habit interventions to overcome students' knowledge-behavior gap.

Method

Research setting

This study was conducted at the Faculty of Health, Medicine, and Life Sciences (FHML) at Maastricht University, which is a public research university in the Netherlands. At Maastricht University (UM), the academic year is divided into six different blocks (i.e., teaching periods), including different thematic courses lasting between four to eight weeks. Courses usually consists of lectures, tutorial sessions and are finalized with an exam. The tutorial sessions are structured according to the problem-based learning (PBL) approach. Within this approach, authentic scenarios are central to learning (Dolmans et al., 2005). In small tutorial groups, ranging from 10-12 students and one tutor, students are introduced to these scenarios according to a seven-step model (Moust et al., 2005). The first five steps, (1) term clarification, (2) problem definition, (3) brainstorming explanations, (4) structuring and analyzing the identified explanations, and (5) formulation of learning goals, take place during the tutorial session. Students then individually study literature to answer their learning goals during (6) self-study. Lastly, during a next tutorial session, students integrate and discuss findings from their self-study in a (7) post-discussion.

Admission to the medical program at UM is a selective procedure, with only limited places available. Students are only eligible if having followed a certain combina-

tion of STEM courses during high school. Furthermore, potential candidates have to undergo two selection rounds. In the first selection round, students' high school transcripts, curriculum vitae and a written assignment are evaluated. If of sufficient quality, candidates are invited to a second selection round, which is an assessment day at the university, where potential candidates have to fulfill various assignments during which their cognitive and (inter)personal characteristics and skills are assessed. Based on these criteria, students are ranked and selected. Admission to the biomedical program at UM was not selective for the cohort participating in this study. The only eligibility criterion was that students had followed a certain combination of STEM courses during high school and were proficient enough in English.

The majority of first-year FHML students at UM are assigned to a mentor and receive a formal learning strategy training in their first weeks ("Study Smart"; Biwer & De Bruin, 2023) to support their self-regulated learning and professional development. The learning strategy training consists of three 90-minute small-group training sessions with different goals. In the first session, the main goal is to increase students' awareness about effective and ineffective learning strategies, why certain strategies work better, and possibly misleading experiences that students might encounter when using (in)effective learning strategies. During the second session, students are asked to try-out different effective learning strategies and think about a concrete plan, how they could incorporate these during their self-regulated learning. During the third session, which is held a few weeks after the previous sessions, students are asked to reflect on their learning strategy use during their self-regulated learning and how they could improve. Throughout the year, students meet with their mentor and write a portfolio reflecting on their competencies related to program content, professional- and study behavior.

Participants

Twenty-nine first- and second-year medicine (n =14) and biomedical sciences (n =15) bachelor students participated in one of six focus group discussions. Students were on average 20.1 years old (14% male). Students were recruited via multiple channels. The first author contacted the mentor and course coordinators of the respective bachelor programs to share the study information with their students. Additionally, students were recruited via posters and approached after tutorials and lectures. During the recruitment phase, the study goal was advertised as exploration of students' study methods and habits. We obtained written informed consent from all participants prior to the study. Participants completed a demographic questionnaire inquiring about their age, study program and year, and grade point average (GPA). Students' GPA ranged from 5.8 – 9, with the mean GPA being 7.4 (on a scale from 1 – 10, with 10 being the highest). Two students did not indicate their GPA. The faculty's ethical review board (FHML-REC/2022/049) approved the study. Students received a small monetary reimbursement to compensate for their participation.

Focus Groups

Students who completed the demographic questionnaire and indicated their availability were invited to the focus group discussions at university. The focus groups lasted approximately 80 minutes (M = 78.4 min, SD = 4.2 min) and were moderated and observed by the first and second author. Based on a semi-structured focus group guide (see Supplementary Materials), students were asked which study methods they usually used during their self-study, what a typical study day looked like, and about their experiences with forming and breaking habits. The clarity of the questions within the focus group guide was piloted with two students prior to the focus group discussions. Based on their feedback, the wording of the questions was slightly adjusted to improve clarity. The first four focus groups were held at the end of students' first-academic year. Two additional focus groups were held at the beginning of students' second bachelor year. The focus group guide was adjusted before the second part of data collection as we noticed that students had difficulties reflecting in-depth on their experiences with forming and breaking habits. Therefore, we created three vignettes describing concrete examples of how a habit was broken or formed based on students' reflections during the first focus groups. Data was collected iteratively and occurred simultaneously with data analysis. In line with Morse (2015), as soon as we estimated our data to be sufficiently rich to gain a deep understanding of students' study experiences and their habit-breaking and -forming experiences, we determined data saturation and stopped data collection. Data saturation is commonly an interpretive judgment in thematic analysis (for a critical stance regarding the concept "data saturation", see Braun & Clarke, 2019). In our case, we started data analysis by descriptive line-by-line coding of the so far collected transcripts, clustering these codes, and searching for patterns, simultaneously to data collection. Based on the understanding we gained during these first analytic steps, we determined to have collected sufficient data to understand students' experiences after six focus groups.

Data analysis and coding procedure

All focus groups were audio recorded and transcribed verbatim. Based on the thematic analysis approach (Braun & Clarke, 2006) we analyzed the focus group discussions inductively. Our analysis was data-driven and thus, the theme development did not mirror our question guide nor do the themes fully align with our potential pre-existing assumptions about students' study habits (Braun & Clarke, 2006; Kiger & Varpio, 2020). We used pre-existing theories to establish our focus-group guide and kept this knowledge as sensitizing concepts during the coding procedure (Bowen, 2006). We conducted a semantic analysis of participants' accounts by interpreting their explicit meanings as recorded and transcribed. After thoroughly listening to the audio recordings and reading the transcripts in-depth multiple times, they were descriptively coded line-by-line using Atlas.ti (version 23.0.7.) by the first author (an extract of our codebook is included in the supplementary materials). Using these descrip-

tive codes, the second author coded 50% of two transcripts without insights into the first coder's line-by-line coding. The outcomes and coding alignments of these partial transcripts were discussed and definitions of codes were further specified, if necessary. Then, patterns within and across focus groups were discussed within the whole research team based on summaries of the transcripts and clustering of the descriptive codes done by the first and second author. Based on this discussion, the first and second author formulated themes, which were reviewed and refined with the entire research team. Additionally, the formulated themes were checked against the coded data and original transcripts. Throughout the analytic procedure, our research team engaged in regular discussions and asked for feedback from scholars outside of the research team during roundtable sessions and conference presentations to critically examine interpretations and findings. We followed a pragmatist approach in analyzing the data, prioritizing the practical relevance of knowledge instead of attempting to explain "reality" (Cherryholmes, 1992). The pragmatist approach offered us the flexibility and adaptability of addressing our research questions as well as generating practical implications from the identified themes while interpreting the data within our specific context.

Reflexivity statement

LD is a PhD student who completed a Bachelor's degree at Maastricht University and is therefore familiar with the UM system also from a student perspective. FB is an educational psychologist with research interests in self-regulated learning and teacher professionalization and knows the PBL system in their role as mentor and tutor. RC is a cognitive psychologist with research expertise in behavior change and technology. AdB is an educational psychologist with research expertise in self-regulated learning in higher education. RC and AdB know the PBL system in various roles (student, teacher, mentor). We are aware that the findings of this study are co-created by interactions between the authors and participants. We thoroughly discussed each process step with all team members and discussed intermediate findings with educational scientists outside of the team and continuously reflected on the extent to which our individual personal experiences and beliefs shaped the research project.

Findings

We clustered students' experiences into five themes: Goals Matter, Balancing Perceived Efficiency and Effectiveness when Studying, Navigating Student Life: from Structured Routines to Self-Regulation Challenges, the Quest for Effective Habits with Trying to Break Free From the Screen as subtheme, and the Motivation Roller Coaster.

Goals Matter

Students mentioned various goals, which influenced their study behavior. Many students had a clear short-term goal of passing the exam in mind. For them, studying during the course served the goal of "collecting all the information" (Student studying medicine (MED), focus group (FG) 2) to prepare for tutorial sessions. Studying for the exam served the goal of "actual studying" (Student studying biomedical sciences (BMS), FG2), during which information is memorized or learned. Students experienced more pressure when studying for an exam compared to studying during the course. Approximately 1.5 weeks before an exam students started intense studying. During this period, they dedicated extensive time to studying, often sacrificing work-life balance and reducing time for activities like exercising, socializing, and hobbies.

Other students indicated having clear long-term academic goals such as receiving a high GPA or wanting to become a good doctor. These clear long-term goals helped them to study consistently, be less-exam oriented, and prioritize their studying also during the course even if having to sacrifice other activities. Instead of studying solely to pass exams, students explained to be more consistent in their study behavior and tried to understand and learn the content continuously. They mentioned achieving this by planning and spreading their study load throughout the course. For example, one student mentioned:

"I don't study for exams anymore, I study because I want to be a good doctor. And I think that mindset also helped me change. [...]. So it's harder to find time around [studying], but I also prioritise [studying], university is the most important thing for me. If it means I don't go to a party or I don't go to the gym, which I also want to do, then that's just how it is." (Student MED, FG5)

Balancing Perceived Efficiency and Effectiveness when Studying

Students generally had quite accurate metacognitive knowledge and were aware that active learning strategies and distributed learning sessions were more effective for long-term learning. Contrastingly, students did not necessarily use those strategies as they experienced that their own study strategies "work" (multiple students in multiple FGs) and were most efficient in reaching their short-term goal to pass the exam or having a strong habit of using them. For example, one student mentioned:

"Well, I know it's not really useful. But I still [summarize] a lot. But I know that it's [...] been proved that it's not really effective. But I still, I don't know, it's just a habit. [...] And it works." (Student MED, FG 3)

Students differed in which strategies they deemed to "work" (multiple students in multiple FGs) for themselves. For tutorial preparations, students usually read and summarized the provided sources. For exam preparations, students used various active and passive learning strategies such as re-reading, summarizing, creating mind

maps, watching videos, recalling information, testing themselves by using past exams or creating flashcards, and explaining content to others or themselves. The amount of practice testing students used during their self-study depended on the availability of past exam questions in their study program as students experience creating practice questions themselves as too time consuming:

"Some of our professors, they made [...] really extensive kind of quizzes with lots of questions. And that was really helpful. I wish they did that for everything." (Student BMS, FG6)

To optimize their study efficiency, next to using cognitive learning strategies, students tried various resource-management strategies, such as creating a planning for their tasks or studying with friends to stay motivated but often faced challenges in accurately managing their time and effort. Students usually started their study session by creating a planning or to-do list, but it was difficult to accurately know how long a task would take or to "really stick to it" (Student BMS, FG3). Instead of studying until a certain time, students usually studied until the task was finished or they could not focus anymore.

Navigating Student Life: From Structured Routines to Self-Regulation Challenges

Students reported basing their study habits on what they had learned during high school, despite university being experienced as different. Next to the content being perceived as more in volume and difficulty, students also mentioned having to adjust to the change of setting. During high school, students often had a structured daily routine. When transitioning to university, they had to adjust to the lack of structure and external control, but also higher flexibility associated with student life. While students appreciated this increased freedom, it also came with the challenge of managing themselves and self-regulating various aspects of life: starting to study, moving to a new city, looking for new hobbies and friends, or managing their household.

"When I lived with my parents in high school [...], you have like a whole routine. [...]. Now you can do things whenever you want to do it. And [...] sometimes you have parties on Monday or on Wednesdays. So, it's on random days. Yeah. And then you're tired on Tuesdays. So, then you don't do as much as other days. [...] I think, it's also part of student life." (Student MED, FG2)

Some students solved the lack of structure by actively creating more external structure in their daily life by joining committees, making appointments with others, or creating a clear separation between work and "personal" life. For other students, the lack of external structure seemed to negatively influence their willingness to form habits as they experienced habits as restricting flexibility. Some students appreciated the flexibility that they associated with student life and did not report actively looking

for more structure. In search for more structure, students differed in their habit and preference of study location. Some students preferred to study at home to avoid distractions, whereas others preferred to study at university as they found it easier to initiate studying with others around and appreciated a separation between their studying and their living space. During courses, students were more flexible in their study setting.

The Quest for Effective Habits

Even though students experienced their current strategies to "work" for the exam, they reported intentions to change their current study behavior. These intentions targeted improving time-management, such as following their planning, procrastinating less, cramming less, limiting screen time, and changing their sleeping schedule. They mentioned making study appointments with others, which helped to feel more accountable, and promoted adherence to intended behavior. Students also mentioned wanting to add steps to their current study habits such as completing their study notes or creating flashcards after each tutorial. For example, a student mentioned "I first had to [...] talk about this topic, answer the question, then I was allowed, for example, to go to the bathroom" (Student BMS, FG4) or working through flashcards when traveling. While students had intentions to change, they mentioned not necessarily prioritizing working on realizing their intentions since their current habits were sufficient to pass their exams but also encountering difficulties when trying to realize them. Students identified various reasons for this. For example, difficulties in creating a feasible planning, following their intention when not being motivated, or falling back into old habits when experiencing a setback. Whilst having good intentions, students perceived change to be effortful, time-consuming or being insecure about whether a change would actually lead to an improved outcome. For example, one student mentioned:

"It's not enough to have motivation to change that one point. Because it's what you say, how do you make the change? By doing it daily. [...]. That's, you know, what I'm trying to do. Like be more consistent. [...]. I'll do great for the first couple of days, maybe two weeks, if I was really motivated. But then after I wake up on a bad day, I really don't feel like it. And it's this boring topic. I'll push it back. [...]. I'll do something else. Then time runs out. Then we're already kind of back in the bad cycle of procrastinating on everything. [...] If there's not the stress of a deadline, then it comes down purely to motivation every day." (Student BMS, FG3)

Trying to Break Free From the Screen

One particularly challenging habit students tried to break was their smartphone habit. Students mentioned turning to their phones or study unrelated websites automatically when lacking focus or procrastinating. This was experienced as distracting and negatively influencing students' studying. They tended to spend more time on their

phone than anticipated, for example, if wanting to briefly check something. To reduce this automatic use, students tried to discontinue their habit by re-structuring their environment so that the distraction would be less accessible or interchanging their phone use with another activity such as reading. Instead of having their phone on the table when studying, they put their phone out of sight, blocked or deleted apps in the morning or exchanged their phone with a friend's phone. Even though students used various strategies to reduce the distraction from these devices, students continuously struggled in limiting their screen time.

"I am so done with my phone being the hugest distraction in my life at this point, it just annoys the hell out of me. I'm actually breaking a habit right now, it's called 'no Instagram anymore'. Yes, it's very bad, but I am... I'm not going to say I am improving because I am not, but I am trying to improve." (Student BMS, FG6)

The Motivation Roller Coaster

Students described experiencing a fluctuation in motivation throughout a course and year, which influenced their study behavior and behavioral change intentions. With their past stressful exam preparation in mind, students reported beginning a new course with many resolutions wanting to improve what went "wrong", such as aiming to study more consistently or to start exam preparations earlier. Students often managed to realize their resolutions for the first few weeks of a new course. However, after approximately two weeks, students lost motivation and started to slack with their studying (e.g., studying less consistently). They experienced less pressure to study, and thus experienced more motivational conflict when initiating studying due to tempting alternative activities, other course obligations, or interferences outside of university. For example, one student, being well aware of the consequences of procrastination, mentioned:

"I can relax now and do this fun thing. And then maybe have to do like, a quick version of this assignment late at night." (Student BMS, FG3)

Three weeks prior to the exam, students felt increased pressure when realizing how close the exam and how much work was left. This pressure motivated students to catch up on the coursework and spend more time studying. Often, students focused on getting the studying done (e.g., creating summaries for each case) and cramming the content using methods that previously worked to pass the exam. For example, one student mentioned:

"I'm also motivated in the beginning of a new block. [...] I have this motivation over me. Like, well, now I'm going to keep up with it. And then sometimes, [...] I lose track of the course that we're in. And I'm behind again. And then I lose it a bit. So, when I get behind, and I'm like, okay, now I just do the minimal. And then two, a week and a half, before the exam, then I get my motivation back." (Student MED, FG2)

Discussion

This paper outlines the findings of a study exploring university students' study habits during self-regulated learning. We held focus groups aiming to explore university students' current study habits, habit formation, and experiences with breaking habits. A thematic analysis of the transcribed data revealed five themes and one subtheme, which offer insights into our research aims regarding how students usually form new habits, and how they (try) to break ineffective habits. Our study offers a detailed exploration of university students' study habits. Using a qualitative approach, we were able to dive beyond surface-level observations by exploring students' experiences and factors, which influence these habits, their formation, and the challenges associated with breaking habits in-depth. While our chosen approach allows for a rich and nuanced understanding of the multifaceted nature of students' study habits, the goal of a qualitative approach is commonly not to generalize findings to a larger population (Morse, 2008). The findings of this study are experiences from a specific student population rooted within a specific educational and cultural context. Including a thick description of this context, we try to establish transferability of our findings by indicating how they could apply to other contexts and student populations.

Students' study habits

Students had different study habits depending on their goals. Students with clear short-term goals of passing the exam focused on collecting information during the course and started intense studying shortly before the exam. Students with long-term academic or career goals planned their study sessions continuously and focused more on learning the study content. Students differed in their preferred study setting when preparing for exams, but usually had a habit and preference of where and how to study. During courses, students were more flexible in their study setting. These findings suggest that long-term academic goal-setting helps students to prioritize long-term learning by spreading out study sessions and focusing on learning the study content continuously. Long-term academic goal-setting might be more evident for some study programs than for others. In study programs such as medicine, many first-year students have a clear goal of becoming a good doctor with long-term retention of knowledge and skills as important factors to reach that goal. Study programs with more diverse career paths might make it difficult for students to envision clear long-term goals. This lack of long-term goal-setting might hamper students' motivation to ensure more effortful studying in a manner that ensures long-term retention or best possible grades. Previous research indicates that students' long-term perspectives are related to better self-regulation strategies (Bembenutty & Karabenick, 2004; De Bilde et al., 2011).

Students tried to be strategic in their learning strategy use by balancing perceived efficiency and effectiveness of the methods in reaching their goals. For tutorial preparations, students usually read and summarized the provided sources. For exam prepa-

rations, students combined active and passive learning strategies such as summarizing, watching videos, or explaining content to themselves. Unlike often assumed in the literature (e.g., Morehead et al., 2016; Yan et al., 2016), students in the current sample had quite accurate metacognitive knowledge. This could be related to the fact that they followed a formal learning strategy training at the beginning of their studies or the PBL system employed at UM, which aims to foster an active learning approach (Dolmans et al., 2005). Students might have been aware of effective and ineffective learning strategies and received suggestions on how to incorporate as many active learning approaches as possible within their self-regulated learning. Nevertheless, they used learning strategies, which are not the most effective for long-term learning but ones that they deemed most time-efficient to pass exams. While students were often aware of this discrepancy, assessment forms were an important driver for learning strategy choices. This is in line with prior research indicating that students adapt their learning strategies to examination requirements (Broekkamp & Van Hout-Wolters, 2007; Rovers et al., 2018). Bachelor students are often assessed using multiple-choice questions, which focus on recognizing information instead of retention. They thus use learning strategies to maximize success for that assessment type. In order to nudge students to use learning strategies essential for long-term learning, it is crucial to align assessment by using methods that stimulate long-term learning and prioritize testing understanding instead of recognition (Van der Vleuten et al., 2010).

Furthermore, students' willingness to incorporate active learning strategies such as retrieval practice seemed dependent on the available resources in their study program. In the medicine program, students had access to old exam questions and thus used them during exam preparations. Students in the biomedical sciences program, having no access to previous exam questions, found it difficult and time-consuming to create practice questions themselves and appreciated course coordinators who provided example questions. This suggests that more support from educators, such as providing practice questions or training sessions on formulating practice questions, might further increase students' use of active learning strategies.

Forming and Breaking Habits

In line with previous research, students reported basing their study methods on what they had learned during high school (Dirkx et al., 2019). They updated these methods if they did not help them to achieve their goals by trying to embed additional steps in pre-existing habits (e.g., if going to bed, then reading notes). This method of specific if-then plans also called implementation intentions (Gollwitzer, 1993; Adriaanse & Verhoeven, 2018) is commonly suggested to foster habit formation and habit breaking. By pre-selecting a situation and mentally rehearsing the if-then link, individuals are more likely to automatically trigger the desired behavior when encountering the situation. Formulating these if-then plans could create new associations that compete with existing habits. If the new cue-action link is stronger than the habitual pattern, the desired action could potentially override the habitual response.

While research across various domains supports the effectiveness of implementation intentions in promoting goal-directed actions (Adriaanse et al., 2011; Gollwitzer & Sheeran, 2006), it is unclear whether implementation intentions influence learners' learning outcomes or metacognition (Hoch et al., 2020).

Students reported intentions to change their study behavior. While their intentions targeted mainly improving time-management aspects or wanting to add steps to their current study habits, disentangling the extent to which students wanted to realize these intentions was difficult. Additionally, detailed reflections of how students broke past ineffective habits and whether they actually changed their behavior once their habits did not "work" anymore remained scarce, making it difficult to fully target our third research aim. Students did not see change as a priority because their current method "worked" to pass exams. As mentioned above, assessment was an important driver for students' learning strategy choices but also a key factor in their behavioral change intentions. Students were successful in passing exams and thus did not perceive change as necessity or added benefit. However, they also indicated not knowing how to change, or experiencing change as effortful and time-consuming. The difference between not changing because perceiving change as having no additional value or because not knowing how to, has important implications for behavioral change interventions. Students who do not perceive change as beneficial might profit from interventions that highlight the utility value of effective learning strategies (e.g., McDaniel & Einstein, 2020) in achieving a sufficient grade to pass a course as efficiently as possible. Students who do not know how to change might profit from interventions that provide them with information on how behavioral change could be achieved. More research is necessary to disentangle the extent to which students are willing to form new and break old habits and if so, how they could be best supported in this.

Another factor influencing students' intention to change and breaking old habits was their fluctuating motivation throughout the course. Students began a new course with many resolutions wanting to improve what went "wrong" the block before but motivational conflict and their usual context quickly disabled them from realizing their intentions and instead continuing with unwanted behavior. In line with Verplanken and colleagues (2018), this finding suggests a potential importance of temporal considerations in behavioral change interventions in transition periods. Interventions held at the beginning of a new course might benefit from students' increased motivation to change.

Additionally, students' capacity to form new and break old habits seems to be influenced by their transition to a more independent environment. During this transition, they did not solely focus on establishing effective study habits but also had to navigate their flexible schedule during which they encountered other self-regulation challenges. According to the Habit Discontinuity Hypothesis (Verplanken & Wood, 2006), major life events or disruptions can serve as catalysts for behavior change, indicating that the transition to university could potentially serve as a great opportu-

nity to break existing habits and form more adaptive ones. As the transitions create a habit discontinuity, people change their habits and adopt new behaviors as old cues and routines that support existing habits are weakened or disrupted (Verplanken et al, 2018). As a result, individuals are more receptive to new opportunities to establish new habits or modify existing ones. This suggests that it might be valuable to support students in building effective habits as soon as they start university to make use of the discontinuity of existing habits, or, as mentioned above, at the beginning of a new course later in the semester. Contrastingly, our findings suggest that the new context and flexibility also challenge the formation of new habits, since it is difficult to "piggy-bag" new habits onto existing ones and because the needs for what makes learning effective to pass exams in the new context are not clear yet. Students solved this by actively looking for more structure. More research is necessary to investigate how the transition to university influences students' capacity to form new habits.

Another factor, which could be important in students' study habits and breaking and formation hereof, is co-regulation. The latter describes how learners' cognition, emotions, and motivation during learning are influenced by interaction with others (Bransen et al., 2022; Hadwin & Oshige, 2011). Students mentioned making study appointments with others, which helped them to feel more accountable for their actions and thus promoted adherence to their intended behavior and could be an important factor in supporting students to break ineffective habits and form new habits. Additionally, observing how others study could help students to model adaptive behavior from peers and thus help them to form habits that incorporate more effective learning strategies. Furthermore, being able to exchange experiences with peers during the habit formation and breaking process, which might be associated with negative emotions such as stress and frustration could help students to cope and stay motivated during their behavior change journey. However, more research is necessary to investigate how co-regulation could influence students' study habits.

Strengths and Limitations

Our findings highlight the central role of students' goals in shaping their study habits. Knowing how goals influence study habits offers valuable insights into the importance of tailoring educational strategies to better align with students' goals and to shed light onto goal-driven behavior in education. Furthermore, the discrepancy between students' knowledge and behavior when it comes to the limited application of effective learning strategies seems to stem from the low perceived efficiency of these strategies. Highlighting a need to increase students' perceived efficiency of effective learning strategies to close the gap between knowledge and behavior. Furthermore, the identified challenges related to motivation fluctuations within and throughout a course and the transitioning from high school to a self-regulated learning environment in university present original perspectives, which so far remain underexamined in the context of self-regulated learning. Our study offers valuable insights into the dynamic hurdles that students face when attempting to modify their study

habits and highlights the importance of aligning assessment methods with life-long learning goals. However, this study has various limitations. First, we conducted convenience sampling. We did not target a specific target population but all first-year biomedical sciences and medicine students were eligible to participate. As the study goal was advertised as an exploration of students' study methods and habits, it might have been possible that especially students who were more confident in their study methods or habits participated leading to a biased perspective. While we cannot rule this out, students were openly sharing that they engaged in methods that they thought were not the most effective and also mention not currently wanting to change their habits. Furthermore, students' self-reported GPA ranged from 5.8 – 9, suggesting a mix between low- and high-achieving students. Additionally, the students' in our sample received a formal learning strategy training in their first weeks to support their self-regulated learning and professional development, which potentially shaped their study behaviors and perspectives and thus outcomes of this study. Next to this, we did not split students from the two different study programs but mixed them within our focus groups. As mentioned above, the structure of the study programs might have shaped the results and further research is necessary to investigate to what extent these findings transfer to other study programs. Second, we held four focus groups at the end of students' first academic year and two focus groups at the beginning of students' second academic year. This change in context might have influenced students' perspectives on their study methods and habits. Future research is necessary to investigate to what extent students' study methods and habits change throughout their study program. Third, we asked students to reflect on their habitual behavior. As habits are often unconscious, we did not explicitly ask students about their habits but instead asked them to reflect on behavior they usually engaged in. The fact that we did not offer any definition of what counts as a usual behavior, might have led to different interpretations hereof. While not the goal of this study, a quantitative research design capturing students' habitual behavior could give more systematic insights by clearly defining and operationalizing the concepts of "usual behavior" in measurable terms. For example, it could be operationalized as behaviors that participants engage in at least three times a week or behaviors that they have engaged in consistently for the past six months or using the Self-Report Habit Index (SRHI, Verplanken & Orbell 2003).

Conclusion

Overall, this study contributes to the literature by providing a qualitative exploration of university students' study habits, formation hereof, and difficulties they experience when breaking habits. A thematic analysis of six focus groups indicated that students had different study habits depending on their goals. While showing accurate metacognitive knowledge of what are effective learning strategies, students often used other learning strategies they deemed most efficient in reaching their goals. Students indicated intentions to change but did not prioritize change as their current habits

enabled them to pass exams and change was not perceived as adding value. Fluctuations in motivation across courses and transitioning to a self-regulated life hampered students' intentions to form new and break old habits. The findings give insights into influential factors affecting students' behavioral change intentions and suggest the importance of aligning assessment methods with life-long learning and supporting students in their long-term academic goal-setting to prioritize study habits that target lasting learning to optimally foster students' self-regulated learning.

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Appendix A. Supplementary Material - Focus Group Guide used for Focus Groups 1-4

Part 1
Understand what a usual study session of students' looks like in terms of where they study, what methods they use and how they initiate and stop a single study session.

Can you describe how you usually study?
(e.g., think about where and when you usually study & what you usually do to prepare for tutorials & study for exams)

Structure	Content / Learning Strategies
Study Environment & Setting: - Where do you usually study? - When do you usually study? - In which social setting do you prefer to study? (e.g., studying with friends, studying alone)	What learning strategies do you usually use during your self-study? - Why do you use these methods? - Have you tried using other methods? - To what extent do these methods work for you?
Considering your described study behavior, what are things that you always do? Are there any exceptions?	
Single Study Session Level: Study Preparation: - How do you usually prepare to start studying? - Is there something you always do to start studying? If so, what do you do? Study Wrap-Up: -How do you decide to stop studying? - Do you usually reward yourself after studying? If so, with what?	

Part 2
Understand whether students follow a study routine, how they formed this, whether they ever tried to change their routine and if they use any external help for this.

Why did you start studying like the way you described (in part 1)?

Formation "Good" Habits:
- Can you tell us more, about how you formed this routine?
- Unrelated to studying, have you ever tried to build a new routine?
- How did you try to build a routine?
    - How did you experience this?
    - Did it work?
    - Was it difficult? If so, why?
    - Did you use any rewards?

Change "Bad" Habits:
- How satisfied are you with your study routine?
- Is there anything you would like to change about your routine?
    - What do you want to change and how would you like to do this?
- Unrelated to studying, what are your experiences with changing/breaking a routine?
    - How did you try to do this?
    - Was it difficult? If so, why?

External Help:

- Did you use any "external" help while changing or forming your routine? (e.g., friends, mentors, apps, podcasts, youtube, tips via social media)
    - How did this help?

Appendix B. Supplementary Material – Example Codes

We included a table with extracts of the descriptive semantic codes we created as part of our initial inductive coding. The codes are organized per theme. The code book extract below represents 32% of our total codes.

Theme	Code
Balancing Efficiency and Effectiveness	Difference preparation exams and tutorials
Balancing Efficiency and Effectiveness	Expectations University Level / assessment method influences study method
Balancing Efficiency and Effectiveness	Expectations University Level / availability of good resources
Balancing Efficiency and Effectiveness	Study method / being (time)efficient
Balancing Efficiency and Effectiveness	Study method / difference between what is effective and what one does
Balancing Efficiency and Effectiveness	Study method / explaining to oneself; others
Balancing Efficiency and Effectiveness	Study method / highlighting
Balancing Efficiency and Effectiveness	Study method / interleaving
Balancing Efficiency and Effectiveness	Study method / mind maps
Balancing Efficiency and Effectiveness	Study method / perception of what is effective; useful
Balancing Efficiency and Effectiveness	Study method / practice testing
Balancing Efficiency and Effectiveness	Study method / recalling information
Balancing Efficiency and Effectiveness	Study method / re-reading through notes
Balancing Efficiency and Effectiveness	Study method / summarizing
Balancing Efficiency and Effectiveness	Study method / videos

Goals Matter	Goal-setting
Goals Matter	Learning / being outcome oriented only
Goals Matter	Learning / having the feeling to forget everything studied
Goals Matter	Learning / learning vs gathering information
Goals Matter	Learning / perception that interacting with the topic is good for learning
Goals Matter	Learning / repetition of topics during academic year; study
Goals Matter	Learning / studying to pass exam vs long-term learning
Goals Matter	Learning / understanding content important
Goals Matter	Preparation for exams / pressure
Goals Matter	Preparation for exams / spread out studying during block
Goals Matter	Preparation for exams / study one week before exam
Goals Matter	Preparation for tutorials / no pressure
Goals Matter	Preparation for tutorials / perceived ease
Goals Matter	Preparation for tutorials / perception that distributing work load is good
Goals Matter	Preparation for tutorials / perception that preparation increases knowledge
Motivation Roller Coaster	Having Finished / feeling of never having finished
Motivation Roller Coaster	Having Finished / finishing work as a priority
Motivation Roller Coaster	Difference in interests
Motivation Roller Coaster	Inducing pressure to be productive
Motivation Roller Coaster	Motivation / differences across; within course; time
Motivation Roller Coaster	Motivation / fresh start
Motivation Roller Coaster	Motivation / initiating working
Motivation Roller Coaster	Motivation / not enough to make change
Motivation Roller Coaster	Prioritizing
Motivation Roller Coaster	Procastination
Motivation Roller Coaster	Procastination / dependent on motivation
Motivation Roller Coaster	Procastination / dissatisfaction
Motivation Roller Coaster	Studying / easier to study if something is interesting

Motivation Roller Coaster	Studying / starting too late
Navigating Student Life	High School
Navigating Student Life	Planning / being flexible
Navigating Student Life	Planning / make appointments with others
Navigating Student Life	Planning / things outside of uni interfere with studying
Navigating Student Life	Priority / study not (only) priority
Navigating Student Life	Routine / difficult to follow routines in all aspects of life
Navigating Student Life	Routine / lack of routine
Navigating Student Life	Routine / lack of routine / satisfaction
Navigating Student Life	Social life
Navigating Student Life	Study location / home
Navigating Student Life	Study location / university
Navigating Student Life	Study location / university / distraction
Navigating Student Life	Study Setting / studying with others
Navigating Student Life	Study Setting / studying alone
Navigating Student Life	Trying to find what works
Quest for Effective Habits	Behavioral Change / change experience
Quest for Effective Habits	Behavioral Change / change not priority
Quest for Effective Habits	Behavioral Change / easy to fall back to old routines
Quest for Effective Habits	Behavioral Change / not knowing how to change
Quest for Effective Habits	Behavioral Change / perception that change is effortful
Quest for Effective Habits	Behavioral Change / perception that change is necessary
Quest for Effective Habits	Behavioral Change / perception that change only necessary if it does not work
Quest for Effective Habits	Behavioral Change / trying to change
Quest for Effective Habits	Behavioral Change / uncertainty about improvement
Quest for Effective Habits	Consistency / difficult to be consistent
Quest for Effective Habits	Consistency / perception that being consistent helps long-term learning
Quest for Effective Habits	Intentions / difficult to follow your intentions

Quest for Effective Habits	Routine / perception that routines help
Quest for Effective Habits	Smart-phone use
Quest for Effective Habits	Study Habit / satisfaction

Chapter 4

Understanding and Supporting University Students' Use of Distributed Practice via Implementation Intentions

An adapted version of this chapter has been submitted as:
David, L., Biwer, F., Crutzen, R., & De Bruin, A. (submitted). Understanding and supporting university students' use of distributed practice via implementation intentions.

Abstract

Effective learning strategies like distributed practice are essential for lifelong learning, yet students struggle to apply them consistently due to habitually using ineffective strategies and poor time-management. Setting goals of when and how to incorporate effective strategies could help bridge the gap between intention and behavior. We tested a goal-setting intervention using implementation intentions to increase students' distributed practice. We tracked daily study behavior of 87 university students (k = 1623) via experience sampling over a four-week course. While formulating implementation intentions did not increase use of distributed practice, students formulating them reported shorter study durations, lower effort, and greater concentration during exam week, suggesting more efficient studying. Regardless of formulating implementation intentions, students adapted to exam proximity by studying longer, reporting higher effort, satisfaction, extrinsic motivation, and more retrieval-based learning strategies. Findings underline assessment as driver for study behavior and provide nuanced insights into students' learning during a course.

Keywords: Learning Strategies, Self-Regulated Learning, Higher Education, Experience Sampling Method, Goal-Setting

Although university students are increasingly aware of and intend to use effective learning strategies, they often struggle to apply them consistently during self-regulated learning (Biwer et al., 2020; Broeren et al., 2024; Rea et al., 2022). Rather than using effective learning strategies such as testing themselves or distributing study sessions, students often rely on passive strategies such as summarizing and cramming shortly before exams (Blasiman et al., 2017; Rea et al., 2022). This is partly due to poor time-management and ingrained habits of using ineffective strategies (David et al., 2024; Rea et al., 2022). The discrepancy between students' intention of using effective learning strategies and their struggle to continuously stick to them highlights a crucial challenge in higher education as it limits students' learning (De Bruin et al., 2023).

One promising approach to bridging the gap between students' intentions and actual behavior is to support goal-setting by implementation intentions (Sheeran et al., 2025). Implementation intentions are specific plans that link a situational cue to a goal-directed behavior (Gollwitzer, 1993, 1999). Implementation intentions have been shown to effectively promote goal-directed behaviors across various domains (Sheeran et al., 2025). Initial interventions explored the application of implementation intentions in higher education settings, particularly to encourage use of effective learning strategies (Breitwieser et al., 2022; Endres et al., 2021; Hoch et al., 2020). However, interventions yield mixed findings and are often not integrated within university students' authentic learning settings.

In the current study, we tested a goal-setting intervention designed to help university students integrate regular distributed practice into their study routine during a four-week course. Furthermore, to capture the dynamics of self-regulated learning (SRL; Zimmerman, 1986), we explored how students regulate their learning in their authentic learning environment. By assessing SRL longitudinally and evaluating a targeted intervention, this study provides new insights into how students regulate their learning over time, and how they can be supported in forming durable, effective study habits.

Effective Learning Strategies in Higher Education

Using effective learning strategies is essential for students' academic achievement and lifelong learning (Bjork & Bjork, 2011; Broadbent & Poon, 2015; Dunlosky et al., 2013). Effective learning strategies are often desirably difficult as they cost initially more effort but result in better long-term learning (Bjork & Bjork, 2011; Bjork, 1994). For example, distributed practice (also known as spaced repetition or spacing) is a learning strategy that involves spreading out learning sessions over time and is widely recognized for enhancing long-term retention (Carpenter et al., 2022; Cepeda et al., 2006; Dunlosky et al., 2013; Theobald et al., 2018).

Students in higher education are increasingly aware of the importance of using effective learning strategies and possess more metacognitive knowledge about these strategies than often assumed in literature (Broeren et al., 2024; David et al., 2024;

Rea et al., 2022). However, despite good intentions, students often fail to consistently apply effective learning strategies during SRL (Blasiman et al., 2017; David et al., 2024; Foerst et al., 2017). This is partly because effective learning strategies, or desirable difficulties, are experienced as more effortful, learning is not always immediately evident, and students easily revert to ingrained habits involving fewer effective strategies (Bjork & Bjork, 2011; Blasiman et al., 2017; De Bruin et al., 2023; Hui et al., 2021, 2022; Kirk-Johnson et al., 2019; Onan et al., 2022).

Another barrier that inhibits students from using effective learning strategies is poor time-management (Blasiman et al., 2017; David et al., 2024; Rea et al., 2022). Implementing strategies like practice-testing, interleaving, or distributed practice requires students to allocate additional time to plan or structure their study materials. For example, when wanting to distribute learning or include practice-testing, students need to start studying early so there is time to space out sessions or account for additional time to prepare testing materials. However, students often struggle to create realistic, actionable study schedules, which undermines their ability to apply distributed practice (Blasiman et al., 2017; David et al., 2024; Rea et al., 2022). For example, Blasiman et al (2017) found a gap between students' intended and actual distribution of study sessions. Students intended to use effective study strategies initially when they believed they would be spending more time preparing for exams, but once exams approached and time was short, students fell back on easier-to-use strategies (e.g., rereading or summarizing). This gap between intended and actual use of effective study strategies due to poor time-management was also confirmed by David and colleagues (David et al., 2024).

These findings suggest that while students may try out effective learning strategies, they often struggle to apply them consistently partially due to ingrained habits and poor time-management.

Increasing Use of Effective Learning Strategies

Several intervention efforts have focused on enhancing students' knowledge and initial use of effective learning strategies (Biwer et al., 2020; Broeren et al., 2023; Theobald et al., 2021). Digital tools, instructional strategies, and metacognitive training programs have been developed to increase students' use of distributed practice (Trumble et al., 2024). For example, spaced-repetition software (e.g., Anki; Elmes, 2025) and digital platforms that automate spaced quizzes, have improved retention and exam performance (Gilbert et al., 2023). Instructional strategies, including frequent low-stakes quizzes and cumulative assessments, have effectively embedded spacing into curricula and reduced students' reliance on cramming (Gurung & Burns, 2019). Additionally, student-centered interventions, such as study strategy training programs, have successfully increased students' use of distributed practice by raising awareness of benefits and providing guidance on initial implementation (Biwer et al., 2023).

While these interventions have been successful in the short-term, many rely on

external structuring (e.g., instructor-designed curricula, technology-driven reminders) rather than equipping students with strategies to build habits and change study behavior durably. Building habits is a key factor in maintaining behavior (Gardner, 2015; Rothman et al., 2009). Hence, interventions focusing on fostering behavioral change and building new study habits could be powerful in helping students transition from intention to sustained application of effective learning strategies (Fiorella, 2020).

One promising approach to initiate behavioral change is supporting goal-setting by formulating implementation intentions (Sheeran et al., 2025). Implementation intentions are a metacognitive strategy in which goal-achievement is supported by extending the goal intention with a detailed plan that outlines timing, location, and methods for initiating actions to support goal-achievement (Gollwitzer, 1993, 1999; Gollwitzer & Sheeran, 2006). This plan facilitates the integration of specific goal-directed behaviors into behavioral routines (e.g., incorporating a specific learning strategy during self-study). For example, students could specify, "If the course lecture is over, then I will review my lecture notes for 15 minutes.". Particularly within social and health psychology, utilization of implementation intentions has proven effective in changing behavior (Gollwitzer & Sheeran, 2006; Sheeran et al., 2025). Research has begun to explore their application in higher education, particularly in encouraging the use of desirably difficulties and time-management (Breitwieser et al., 2022; Clark et al., 2021; Endres et al., 2021; Hoch et al., 2020).

While implementation intentions have been shown to benefit self-regulation in educational contexts (e.g., Bayer & Gollwitzer, 2007; Duckworth et al., 2013; Oettingen et al., 2015; Parks-Stamm et al., 2010; Schunk et al., 2022; Wieber et al., 2011), their effectiveness in promoting effective learning strategies remains inconclusive. For example, implementation intentions do not seem to change university students' learning strategy application, due to students' struggle to formulate high quality implementation intentions (Endres et al., 2021). Contrastingly, implementation intentions aimed at helping medical students achieve their daily goal of studying a self-set number of flashcards resulted in a beneficial effect on goal-achievement (Breitwieser et al., 2022). Similarly, a mental contrasting intervention, during which students had to formulate a goal and plan to overcome a potential obstacle that could hinder them from achieving this goal, increased students' study time compared to those who did not formulate implementation intentions (Clark et al., 2021).

Although evidence remains mixed, the findings suggest that when the quality of implementation intentions is sufficient, they may be an effective tool to benefit students' goal-achievement. By encouraging students to formulate implementation intentions, abstract goals such as "using more distributed practice" are translated into concrete actions which clarify when, where, and how to engage in distributed practice. This structured planning and recurring enactment of behavior cued by a specific context could foster the formation of effective study habits enhancing the consistent use of distributed practice.

Understanding SRL Using Experience Sampling

To evaluate whether implementation intentions translate into sustained goal-directed behavior, it is essential to capture students' goal-achievement and study behavior over time in authentic learning contexts. While traditional pre- and post-intervention measures often overlook temporal variability, an intensive longitudinal approach can capture how students regulate their study behavior across multiple weeks (Breitwieser et al., 2024; Nobbe et al., 2024; Rovers et al., 2019). One method of capturing this is the Experience Sampling Method (ESM). First introduced by Csikszentmihalyi, Larson, and Prescott (1977), ESM captures momentary experiences occurring in their natural context using mainly self-reports. Participants are mostly prompted via smartphones to briefly monitor their current mood, ongoing activities or experiences throughout their day, offering high ecological validity (for a more in-depth introduction to ESM see Myin-Germeys & Kuppens, 2022). ESM's multiple real-time measurements capture context-specific experiences, offering a comprehensive, nuanced understanding of how students navigate and adapt their learning over time. Though not commonly used to assess SRL, ESM is a valuable tool for advancing a holistic understanding of real-world SRL which could potentially provide insights into how to support students in becoming more effective self-regulators.

The current study

We had a two-fold aim. First, as students often struggle to distribute learning over time, we tested whether formulating implementation intentions would increase their use of distributed practice (RQ1). Students in the implementation intention (II) group were guided to specify how and when they planned to incorporate regular review sessions (i.e., distributed practice) in their study routine. Students in the control group received information and tips about distributed practice without formulating plans. We expected that participants in the II group would engage in more distributed practice (use of distributed practice hypothesis). Furthermore, we explored whether participants in the II group scored a higher grade at the end of the course (performance hypothesis) and whether they had a higher intention to incorporate distributed practice compared to participants in the control group (intention to use hypothesis). Our second aim was to gain a better understanding of how students regulated their learning during their self-study and how our intervention influenced this (RQ2). We explored daily fluctuations in study behavior such as strategy use, study duration, and learning experiences such as study satisfaction, study effort, concentration, distraction, and intrinsic and extrinsic motivation. These learning experiences are key aspects of SRL, as they indicate how students reflect on their learning and adapt it over time (Bellhäuser et al., 2019; Liborius et al., 2019).

Method

Transparency and openness statement

This study was pre-registered on the Open Science Framework (OSF; https://osf.io/jbucw/?view_only=a4f2bb80e8b04800a895a4dad50d193d). The data and materials are accessible via OSF: https://osf.io/6bfh4/

Participants & Context

We conducted a four-week ESM study in the 2023/24 semester at Maastricht University within the Faculty of Health, Medicine and Life Sciences. Prior to data collection, we received ethical approval from the faculty's ethical review board (FHML-REC/2024/030). To recruit participants, we approached students during lectures or small-group tutorials and asked course coordinators and mentors to share information about our study with their students. Participating in a graded end-of-course examination was a requirement to participate in the study. A total of N = 87 (females = 77) undergraduate students aged M = 19.9 (SD = 1.85) studying Health Sciences (n = 42), Medicine (n = 27), Biomedical Sciences (n = 10), Regenerative Medicine and Technology (n = 6), or European Public Health (n = 2) participated in the study. Two participants were excluded due to technical malfunction during the randomization process which resulted in them being assigned to neither group.

At Maastricht University, the academic year is organized into six teaching periods, each focusing on a different theme and lasting between four and eight weeks. The present study took place during a four-week period. Despite differences in course topics, the structure and instructional approach are highly comparable across courses and study years. Each course typically combines lectures with small-group tutorials and concludes with a written exam. The tutorials follow the problem-based learning (PBL) model, which emphasizes learning through authentic, practice-oriented problems(Dolmans et al., 2005). Students work in small group meetings with a tutor, during which the problems are discussed and learning goals are developed. These learning goals guide individual self-study during which students try to formulate answers to the learning goals based on the literature they read.

Procedure and Materials

During recruitment, we shared information about our study via Qualtrics. There, students gave informed consent if interested in participation. They also received information on how to sign-up for the study and download the Avicenna Research App (Avicenna Research, 2024), which we used to collect data. After downloading the app, students completed a pre-questionnaire in which we collected participants' age, gender, study program, study year, study course, and exam results of the last three exams as demographic data. Additionally, we asked about their usual study be-

havior (the learning strategies they commonly use, what their focus of learning was, the frequency of studying per week, the number of study sessions per day, and the duration of study sessions) in the starting weeks of a course and again for the two weeks before an exam. Immediately after the pre-questionnaire, participants were randomly assigned to either the II (n = 35) or control group (n = 50). In both groups, participants were informed about distributed practice and received general advice on how to incorporate regular review sessions throughout their SRL. Participants in the II group were asked to formulate implementation intentions on how to include distributed practice in their learning. To guide this process, they were prompted with various questions to set-up a detailed implementation intention. More specifically, we asked them: 1) how and what are you planning to review in the following weeks, 2) when are you planning to review materials in the following weeks, 3) where are you planning on reviewing materials in the following weeks. Additionally, participants in the II group were asked to anticipate obstacles that could hinder them from achieving their goal and think about a method to overcome these obstacles in the form of an if-then plan (Adriaanse et al., 2010; Clark et al., 2021). Participants in the control group did not receive these prompts. Instead, like the II group, they were asked to indicate their intentions of incorporating regular review sessions. On a 5-point Likert scale, participants indicated to what degree they intend to, are willing to, or plan to incorporate regular review sessions into their study routine (cf. instructions available in Psychological Construct Repository; https://psycore.one/construct/?ucid=intention_73dnt604).

After the pre-questionnaire, for four weeks, participants in both groups received one daily ESM questionnaire at 18.00h, which monitored daily study behaviors and goal-achievement. If participants failed to fill in the first prompt, they received a reminder at 20:00h and 22:00h. Following the initial notification, the daily questionnaire could be filled in until 23:59h before it expired. The daily questionnaire consisted of a minimum of two and a maximum of 18 items, depending on certain item responses (i.e., most items were only presented after participants indicated that they had studied that day). If participants indicated that they had studied that day (yes/no question), they were asked how long they studied (continuous scale in minutes), which learning strategies they used (multiple choice item), whether they used distributed practice (yes/no question), whether they had planned to use distributed practice (yes/no question) and their reflections of that study session capturing their study satisfaction (I am very satisfied with the studying I have achieved today), study effort (Today, I made an effort when studying), concentration (Today, during my studying, I was very concentrated), distraction (Today, during my studying, I was very distracted), and intrinsic (Today, I was looking forward to my studying and dealing with its contents) and extrinsic motivation (Today, I was driven to study mainly by the pressure I had; all 6-point Likert scale (Liborius et al., 2019)).

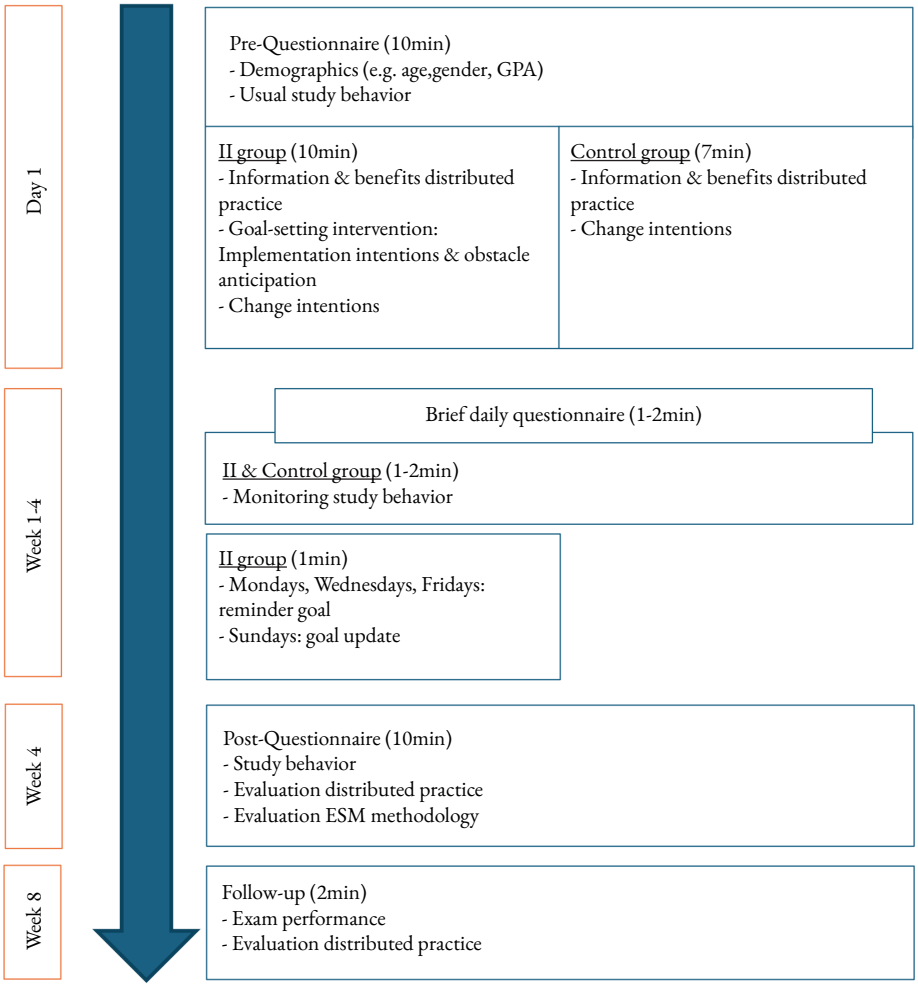
Participants in the II group received a reminder of their goal and obstacle plan every second weekday (Mondays, Wednesdays, Fridays). Once a week, they had the

opportunity to update their goal and obstacle plan. Participants in the control group did not set any goal, received no reminders, and thus no option to update any goal. In total, the ESM period lasted for 17-26 days depending on the starting day of participants and was embedded within one teaching period of our university. This meant that we started the ESM period on the first day of a new course (June 10, 2024), with participants being eligible to start between June 10 – June 19, and stopped at the end of the course (July 5th, 2024). All courses had an exam scheduled at the end of week 4 of the ESM period.

At the end of the ESM period, all participants were asked to fill in a post-questionnaire. In this questionnaire, we asked questions concerning participants' study behavior during the last two weeks of the course using the same questions as in the pre-questionnaire (the learning strategies they commonly use, what their focus of learning was, the frequency of studying per week, the number of study sessions per day, and the duration of study sessions). Additionally, we asked about their experiences using distributed practice, whether they would use distributed practice in the future, their reasons for (not) doing so and experiences participating in an ESM study using open response questions. Finally, we administered a follow-up questionnaire three weeks later, in which participants were asked to indicate the grade they received in the course they followed during the ESM period and their future use of distributed practice. An overview of our study procedure can be found in Figure 4.

At the end of the study, participants were rewarded, receiving increasing voucher incentives from €10 to €40 based on response rates, with no payment for rates below 30% and a maximum reward for response rates of 95% or higher. Participants had access to their response rate and were aware of the reward scheme.

Figure 4. Study Design & Procedure



Analysis

Data collection via ESM yielded k = 1645 observations from n = 85 participants. Three participants were removed due to response rates below 30% and one for not following intervention instructions, resulting in 48 participants in the control and 33 in the II group. An independent t-test showed no significant differences in daily prompt responses between groups (M_{II} = 24.61, SD_{II} = 2.56; $M_{control}$ = 23.63, $SD_{control}$ = 2.77), t(72.36) = -1.64, p = .106. To account for the different starting days of participants, we compared the number of days participants were exposed to the daily prompts between groups in an ANOVA and found no statistically significant differ-

ences between groups (M_{II} = 24, SD_{II} = 1.96; $M_{control}$ = 23.20, $SD_{control}$ = 2.09), F(1, 79) = 1.81, p = .182. Of the 1623 total daily observations, 1061 represented learning occasions. These were aggregated into 317 weekly observations for the main analysis. Quantitative analyses were conducted in R (R Core Team, 2025) using the lme4 package (Bates et al., 2015) for our main analyses. Open-ended questionnaire responses and goals and obstacles from the II group were analyzed qualitatively. After initial reading, responses were clustered and summarized by content. Similarly to Endres and colleagues (2021), we assessed quality of implementation intentions by scoring (0 or 1) whether they included a review session. Furthermore, they were scored (0 or 1) for inclusion of how, what, when, and where students intended to review, and for the specificity of each component rated as 0 (vague) or 1 (concrete and specific; total maximum score = 9). Obstacle plans were coded (0 or 1) for inclusion of an obstacle, a plan to overcome it, and the specificity of each of these rated as 0 (vague) or 1 (concrete and specific; total maximum score = 4).

For the use of distributed practice hypothesis, we aggregated the daily use of distributed practice per week, per participant to a cumulative score representing the total number of days each participant engaged in distributed practice per week (ranging from 0 to 7). We used a mixed-effects model with cumulative weekly score as dependent variable, fixed effects for group (II vs. control), and random intercepts for participant and week. This resulted in the following structure:

cumulative distributed practice ~ group + (1 + week| participant ID).

To investigate whether group differences emerged over time, we re-ran the model above adding a group × week interaction and participant ID as random intercept. For the performance hypothesis, we conducted a linear regression predicting post-test exam grade from group and average pre-test exam grade. For the intention to use hypothesis, we employed a mixed-effects model with weekly cumulative distributed practice as dependent variable, mean intention-to-use scores and group as fixed effect, and random intercepts for participant and week.

To address our second aim, exploring daily learning experiences, we examined fluctuations in study duration, learning strategies, study satisfaction, study effort, concentration and distraction, and intrinsic and extrinsic motivation. While learning strategies were analyzed descriptively, we conducted linear mixed-effects models for study duration and each of the daily self-reported experiences (e.g., study satisfaction, or study effort) as outcome variable, fixed effects for group, week, their interaction, and random intercepts for participants.

Results

The descriptive statistics from the pre-questionnaire for the II and control group are summarized in Table 1. Group comparisons were conducted to examine statistically significant differences between groups in these variables. There were no significant differences in age between the groups, t(67.11) = -1.06, p = .29. A Mann–Whitney U test indicated no difference in study year, U = 700, p = .24. Also, gender distribution

($p = 1.00$) and study program distribution ($p = .74$), assessed via Fisher's exact tests, did not differ between groups. Mann–Whitney U tests showed no significant baseline differences in study days per week ($U = 724.50$, $p = .51$), number of daily study sessions ($U = 657.00$, $p = .16$), minutes per study session ($U = 803.50$, $p = .91$), or study approach satisfaction ($U = 761.50$, $p = .77$). During the exam period, the groups also did not differ in study days per week ($U = 692.50$, $p = .32$), minutes per study session ($U = 825.00$, $p = .75$), or study approach satisfaction ($U = 822.50$, $p = .77$). However, there was a significant difference in number of daily study sessions in the weeks before the exam, with the control group reporting more study sessions than the intervention group ($U = 569.00$, $p = .027$). Fisher's exact tests were used to examine group differences in study strategies used, study focus, and change-wish items. At the beginning of the course, no significant differences emerged between groups for any study strategy or study focus item (all $p > .24$), except that the control group more often reported working on assignments as a study focus ($p = .004$). At the end of the course, the only significant difference in study strategies was that the control group more frequently reported explaining content ($p = .013$). No other study strategy or study focus differences were observed (all $p > .13$). For change wishes, no significant group differences were found at the beginning of the course (all $p > .29$). At the end of the course, groups differed only in the wish to spread out study sessions, which was more commonly endorsed in the control group ($p = .033$). All other change-wish items showed no meaningful group differences (all $p > .07$).

Although a few statistically significant group differences emerged, these seem isolated and did not suggest a systematic pattern, indicating that the groups were largely comparable across demographic and study-related variables. In both groups, in the first course weeks, students mainly focused on tutorial preparation using strategies such as summarizing, watching videos, and re-reading. Toward the end of the course, students in both groups focused on exam preparations, studying longer and more frequently, continuing earlier strategies while also adding active ones such as self-testing and explaining content. The wish to change variable indicated that students in both groups mostly wanted to start exam preparation earlier.

Table 1. Descriptive Statistics per Group

Variable (scale)	II Group (Mean ±SD / n (%))	Control Group (Mean ±SD / n (%))
Age (continuous)	19.79 ± 1.47	19.58 ± 1.07
Gender (nominal)		
Male	4 (12.1%)	5 (10.4%)
Female	29 (87.9%)	43 (89.6%)
Study year (ordinal)		
Year 1	27 (81.8%)	34 (70.8%)
Year 2	5 (15.2%)	10 (20.8%)
Year 3	1 (3%)	4 (8.3%)
Study program (nominal)		
Health Sciences	15 (45.5%)	23 (47.9%)
Medicine	12 (36.4%)	14 (29.2%)
Regenerative Medicine	3 (9.1%)	3 (6.2%)
Biomedical Sciences	2 (6.1%)	7 (14.6%)
European Public Health	1 (3%)	1 (2.1%)
Prior cumulative exam score (1-100)	71.1 ± 9.47	73.4 ± 9.10
Study session (beginning of course)		
Study days per week (0-7)	3.91 ± 1.68	4.15 ± 1.96
Number daily study sessions (continuous)	1.82 ± 1.24	2 ± 0.97
Minutes per study session (continuous)	94.85 ± 60.99	91.04 ± 49.16
Study approach satisfaction (0-10=	5.76 ± 2.31	5.79 ± 2.4
Study session (end of course)		
Study days per week exam (0-7)	5.61 ± 1.20	5.83 ± 1.17
Number daily study sessions exam (continuous)	3.06 ± 1.73	3.54 ± 1.4
Minutes per study session exam (continuous)	114.55 ± 56.85	112.29 ± 56
Study approach satisfaction exam (0-10)	6.82 ± 1.7	6.77 ± 1.82

Variable (scale)	II Group (Mean ±SD / n (%))	Control Group (Mean ±SD / n (%))
Study Strategies (beginning course) (multiple choice)		
Summarizing	21 (63.6%)	27 (56.2%)
Watching videos	18 (54.5%)	25 (52.1%)
Re-reading notes	9 (27.3%)	20 (41.7%)
Highlighting	15 (45.5%)	16 (33.3%)
Explaining content	8 (24.2%)	14 (29.2%)
Re-reading literature	9 (27.3%)	11 (22.9%)
Mind-maps	3 (9.1%)	6 (12.5&)
Self-testing	4 (12.1%)	5 (10.4%)
Repeating content	7 (21.2%)	12 (25%)
Other	2 (6.1%)	7 (14.6%)
Study strategies (end of course) (multiple choice)		
Summarizing	25 (75.8%)	31 (64.6%)
Watching videos	22 (66.7%)	31 (64.6%)
Re-reading notes	21 (63.6%)	38 (79.2%)
Highlighting	10 (30.3%)	15 (31.2%)
Explaining content	14 (42.4%)	34 (70.8%)
Re-reading literature	7 (21.2%)	10 (20.8%)
Mind-maps	9 (27.3%)	12 (25%)
Self-testing	23 (69.7%)	30 (62.5%)
Repeating content	16 (48.5%)	32 (66.7%)
Other	1 (3%)	0 (0%)
Study focus (beginning of course) (multiple choice)		
Preparation for tutorials	30 (90.9%)	42 (87.5%)
Practical preparation	14 (42.4%)	23 (47.9%)
Assignments	11 (33.3%)	32 (66.7%)

Variable (scale)	II Group (Mean ±SD / n (%))	Control Group (Mean ±SD / n (%))
Re-studying content	2 (6.1%)	3 (6.2%)
Exam preparation	4 (12.1%)	7 (14.6%)
Portfolio	1 (3%)	0 (0%)
Study focus (end of course) (multiple choice)		
Preparation for tutorials	9 (27.3%)	17 (35.4%)
Practical preparation	5 (15.2%)	4 (8.3%)
Assignments	14 (42.4%)	20 (41.7%)
Re-studying content	11 (33.3%)	20 (41.7%)
Exam preparation	31 (93.9%)	44 (91.7%)
Portfolio	0 (0%)	1 (2.1%)
Change wishes (beginning of course) (multiple choice)		
Start exam preparation earlier	23 (69.7%)	31 (64.6%)
Spend more time studying	10 (30.3%)	19 (39.6%)
Spread out sessions	8 (24.2%)	17 (35.4%)
Use other study methods	10 (30.3%)	9 (18.8%)
Other	1 (3%)	0 (0%)
I am not sure what to change	5 (15.2%)	10 (20.8%)
I do not want to change	3 (9.1%)	7 (14.6%)
Change wishes (end of course) (multiple choice)		
Start exam preparation earlier	23 (69.7%)	29 (60.4%)
Spend more time studying	10 (30.3%)	12 (25%)
Spread out sessions	7 (21.2%)	22 (45.8%)
Use other study methods	5 (15.2%)	17 (35.4%)
Other	2 (6.1%)	1 (2.1%)
I am not sure what to change	7 (21.2%)	10 (20.8%)
I do not want to change	6 (18.2%)	7 (14.6%)

Note. Values are means ± SD for numerical variables and frequencies with percentages based on total group size (n (%)) for categorical variables.

Goals and Obstacles Formulated by II Group

Qualitative analysis of the II group's goal-setting statements showed that most participants planned to review content through practice-testing, summarization or visualization techniques. For an overview of students' goals clustered according to their planned learning strategies, see Table 2. These activities were typically scheduled shortly after the original learning activity such as following lectures or tutorials (k = 18). Students chose to study either at home (k = 17), university library (k = 9) or did not specify (k = 7). On average, students scored M = 6.48 (SD = 1.82) out of 9 on implementation intentions. Most students included how (88%), what (88%), when (88%), and where (91%) they wanted to distribute their learning. However, only 57% of students provided specific details on how, 36% on what, and 42% on when they planned to review, indicating a lack of specificity.

Students identified barriers that could hinder goal- achievement and formulated if-then plans to overcome these. Obstacle plans showed a similar pattern to goals (M = 2.85; SD = 1.15; maximum score = 4), with all students describing a plan to overcome an obstacle, but only 64% included the obstacle. Overall, 58% of students specifically described the obstacle and only 64% provided a concrete strategy to overcome it. Most frequent obstacles (see Table 3) included poor time-management (k = 12), such as overambitious planning, distractions (e.g., phone use or social invitations) (k = 6), or forgetting scheduled sessions (k = 6).

Table 2. Clustered Goals of Students in the II group

Strategy	Frequency	Example
Making Flashcard/Practice-Testing/Practice exercises	14	"I will create flashboards of the information from the tutorials, the week of the tutorials, at home."
Summarizing Content	8	"I will make a short summary for every learning goal, the day after the post discussion, I will do it behind my desk in my office."
Planning/Scheduling Review	6	"I will plan the Sunday night revision of this week's lectures in my agenda and spend around 1.5 hours doing the revision."
Visualization	3	"I will make a drawing of the material for each case directly after the tutorial group session in my room."
Dual strategy use	2	"I will summarize all the information, start making mock tests, for four hours a day, at home or in the library."

Note. Frequencies indicate the number of students mentioning each strategy. Examples are representative paraphrases from open-ended responses.

Table 3. Clustered Obstacle Plans Students

Plan to overcome an obstacle	Frequency	Example
Allowing enough flexibility in planning	12	"I will dollow the to do list as good as possible but change it when I see it is not realistic die to something else coming up."
Using reminders to avoid forgetting	6	"If I forget my schedule review session, I will set a reminder on my cellphone."
Overcoming distractions by prioritizing	6	"If I think other things are more fun to do, I will remind myself of the benefits of doing things now instead of later."
Creating a planning/to-do list	6	"I will schedule my study sessions in my digital calendar."
Other (asking for help/take rest)	2	"If I come across difficulties I don't know how to solve and I want to stop, I will ask someone to help me look at the problem differently."

Note. Frequencies indicate the number of students mentioning each strategy. Examples are representative paraphrases from open-ended responses.

Research Question 1: Use of Distributed Practice Hypothesis

Descriptive statistics indicated that, on average, participants in both groups engaged in distributed practice on approximately 1.61 days per week (SD = 1.54) with the II group engaging on average on 1.54 days per week (SD_{II} = 1.49) and the control group on 1.66 days per week ($SD_{Control}$ = 1.58; see Figure 1). The model intercept of our linear mixed-effects model, representing average distributed practice scores in the control group at baseline, was β = 1.51, SE = 0.16. There was no statistically significant effect of group on use of distributed practice (β = -0.09, SE = 0.25, p = .712, 95% CI [-0.59; 0.40]), suggesting that formulation of implementation intentions did not lead to increased use of distributed practice among students compared to only receiving information on distributed practice and how to employ it within daily studying.

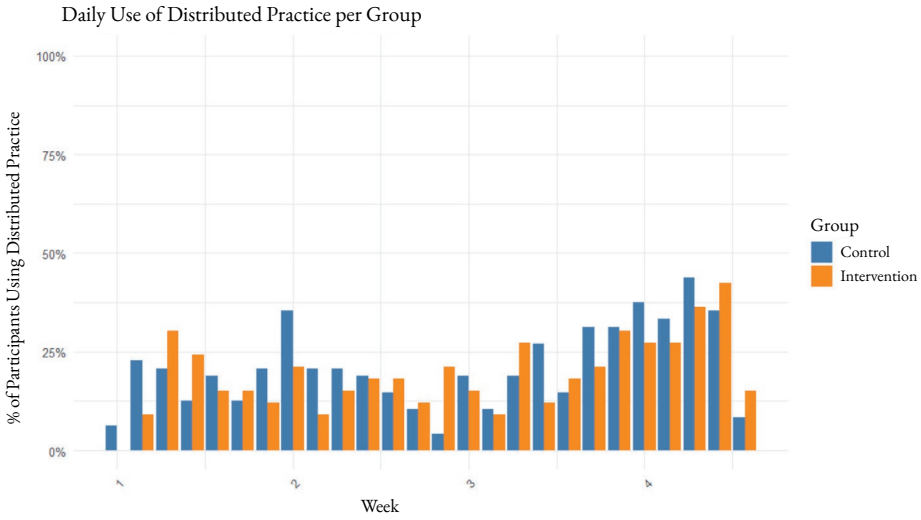
We did not find evidence for group differences emerging over time, as the model did not show a significant main effect of group (β = -0.02, SE = 0.35, p = .945, 95% CI [-0.71; 0.67]), nor any significant group × week interactions (ps > .705). The significant main effects for week 3 (β = 0.59, SE = 0.24, p = .014, 95% CI [0.12; 1.06]) and week 4 (β = 0.93, SE = 0.24, p < .001, 95% CI [0.46; 1.41]) suggest that students in both groups reported significantly more distributed practice in later course weeks compared to week 1.

Research Question 1: Performance Hypothesis

We did not find evidence that the intervention influenced final exam performance as the main effect of group was not statistically significant (β = -2.51, SE = 2.25, p = .271, 95% CI [-7.03; 2.01]), whereas prior performance was a significant positive pre-

dictor of final exam grade (β = 0.57, SE = 0.12, p < .001, 95% CI [0.32; 0.83]).

Figure 1. Daily Use of Distributed Practice per Group



Note. Percentage of participants based on group size that engaged in distributed practice per day throughout the course.

Research question 1: Intention to Use Hypothesis

The independent samples t-test revealed that there was no statistically significant difference in intention to use distributed practice between groups (M_{II} = 3.06; SD_{II} = 0.81; $M_{Control}$ = 3.01; $SD_{Control}$ = 0.85), t(282.29) = -0.51, p = .607, 95% CI [–0.23, 0.14]), suggesting that the intervention did not lead to a higher intention to engage in distributed practice compared to the control group. We did not find a significant main effect for intention to use in our mixed-effects model, suggesting that intention to use was not a significant predictor of use of distributed practice (β = 0.39, SE = 0.19, p = .051, 95% CI [0.005, 0.776]).

Post- Questionnaire Evaluation of Distributed Practice

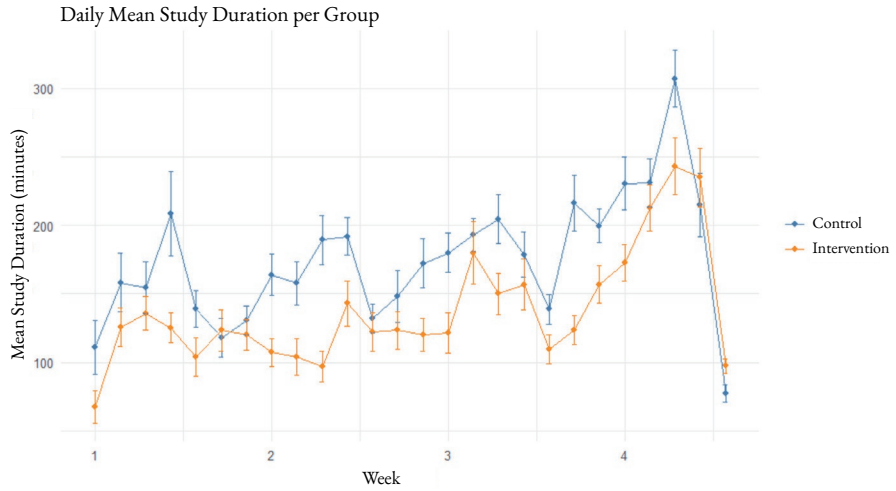
Twenty-four participants in the II group and 42 from the control group filled in the post-questionnaire. Here, 25% (n = 6) in the II group and 23.8% (n = 10) in the control group mentioned not using distributed practice throughout the course. These numbers do not match the daily questionnaire indicating that only one participant (3%) from the II group and five participants (10%) from the control group never used distributed practice throughout the course. This difference between the post- and daily questionnaire indicates a discrepancy between retrospective self-reported use

of distributed practice and actual use measured through the daily questionnaire, suggesting that students may underestimate their use of this strategy when reflecting retrospectively.

Research Question 2: Daily Study Behaviors

The daily questionnaire showed that the II group studied on average on 11.7 days (SD = 5.92), whereas the control group studied on average 14.1 days (SD = 5.12). When studying, the II group studied on average 143.74 minutes (SE = 3.19) per day, the control group for 185.17 (SE = 3.62, see Figure 2). The linear mixed-effects model revealed a significant main effect for group (β = -37.2, SE = 16.97, p = .029, 95% CI [-70.53, -4.00]), suggesting that participants in the II group studied significantly shorter than participants in the control group. The significant main effects for week 3 (β = 27.02, SE = 9.44, p = .004, 95% CI [8.50, 45.53]) and week 4 (β = 100.7, SE = 12.08, p < .001, 95% CI [77.03, 124.39]) suggest that both groups reported significantly longer study duration in later course weeks compared to week 1. The lack of significant group × week interactions (ps > .18) indicated that there were no group differences in how study duration changed over time.

Figure 2. Daily mean study duration per group



Note. Mean daily study duration per group with standard errors.

Daily Study Strategies

Descriptive analyses of strategy use across the four course weeks revealed shared patterns across groups but differences in timing (Table 4). In the first course weeks, both groups used mainly information collection and selection strategies, such as re-read-

ing, summarizing or watching videos. In later course weeks, while summarizing remained common, both groups incorporated more retrieval-oriented strategies such as self-testing and explaining content. Interestingly, participants in the II group incorporated self-testing in week 1 already compared to the control group who started from week 3 onwards. Despite this incorporation of active learning strategies, especially in later course weeks, students still largely relied on summarization and re-reading content.

Table 4. Percentage of Participants in the II Group Using Each Learning Strategy per Week

Week	Respondents II Group	Learning Strategy II Group	n (%)
1	33	Writing a summary	21 (63.6)
		Re-reading notes	18 (54.5)
		Watching videos	16 (48.5)
		Repeating previously learned content	13 (39.4)
		Testing yourself	13 (39.4)
		Re-reading literature	13 (39.4)
2	33	Writing a summary	20 (60.6)
		Re-reading notes	17 (51.5)
		Watching videos	17 (51.5)
		Repeating previously learned content	17 (51.5)
		Testing yourself	13 (39.4)
3	32	Repeating previously learned content	22 (68.8)
		Re-reading notes	18 (56.2)
		Writing a summary	18 (56.2)
		Testing yourself	17 (53.1)
		Watching videos	17 (53.1)
4	32	Testing yourself	17 (53.1)
		Repeating previously learned content	16 (50)
		Re-reading notes	15 (46.9)
		Writing a summary	12 (37.5)
		Watching videos	9 (28.1)

Note. The table displays the five most used learning strategies per week per group. Values reflect the number of participants who reported using each strategy at least once that week (column n (%)), relative to those who completed the daily questionnaire at least once that week (column respondents II group).

Table 5. Percentage of Participants in the Control Group Using Each Learning Strategy per Week

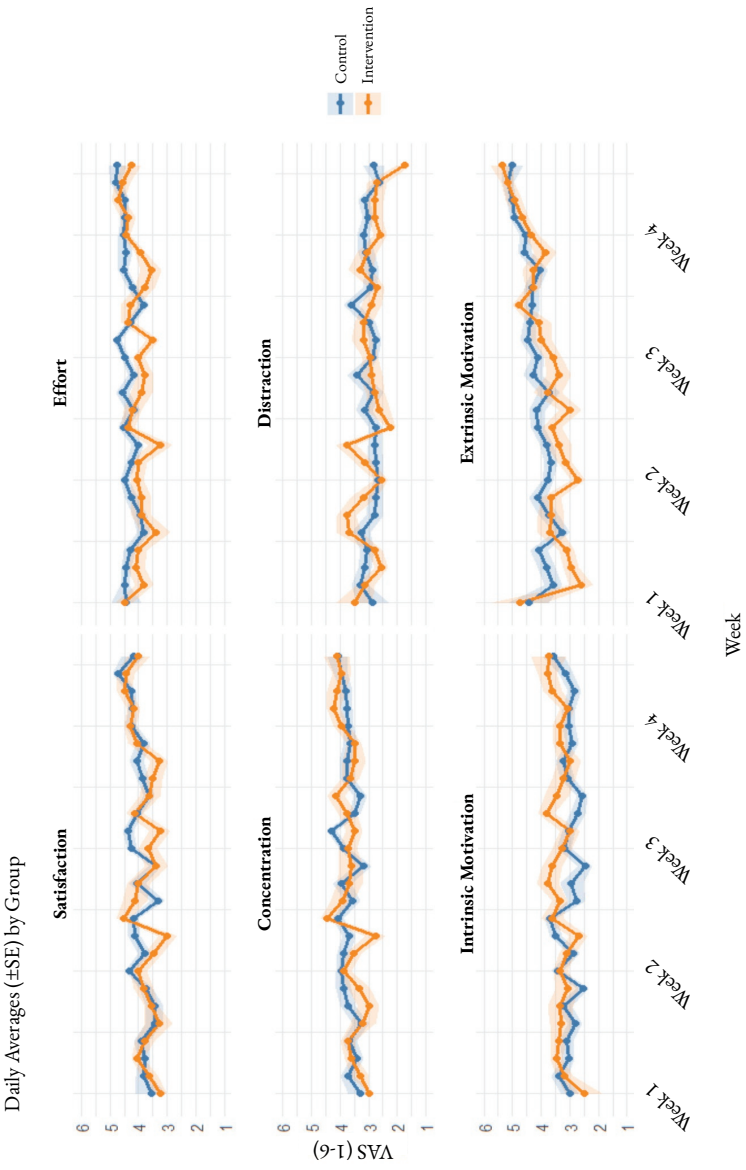
Respondents Control Group	Learning Strategy Control Group	n (%)
48	Writing a summary	36 (75.0)
	Re-reading notes	35 (72.9)
	Re-reading literature	31 (64.6)
	Watching videos	29 (60.4)
	Repeating previously learned content	26 (54.2)
48	Writing a summary	30 (62.5)
	Re-reading notes	29 (60.4)
	Re-reading literature	23 (47.9)
	Repeating previously learned content	22 (45.8)
	Watching videos	22 (45.8)
47	Re-reading notes	33 (70.2)
	Repeating previously learned content	30 (63.8)
	Testing yourself	28 (59.6)
	Writing a summary	27 (57.4)
	Re-reading literature	22 (46.8)
41	Testing yourself	27 (65.9)
	Re-reading notes	26 (63.4)
	Repeating previously learned content	23 (56.1)
	Re-reading literature	16 (39.0)
	Explaining content to yourself/others	15 (36.6)

Note. The table displays the five most used learning strategies per week per group. Values reflect the number of participants who reported using each strategy at least once that week (column n (%)), relative to those who completed the daily questionnaire at least once that week (column respondents control group).

Learning Experiences During the Course

To explore students' day-to-day learning experiences over the four-week study period, we examined daily fluctuations in study satisfaction, study effort, concentration and distraction, and intrinsic and extrinsic motivation. Figure 3 illustrates daily group-level averages of each variable across time with standard errors.

Figure 3. Daily mean averages of learning experiences per group



Study Satisfaction. The control group reported a mean study satisfaction of 4.00 (SD = 1.17) and the II group 3.86 (SD = 1.28). The results of the mixed effects model revealed a significant increase in daily study satisfaction in week 4 compared to week 1 (β = 0.59, SE = 0.14, p < .001, 95% CI [0.31; 0.87]). No significant main effects were observed for the II group (p = .29) or for weeks 2 and 3 compared to week 1 (ps > .20). Similarly, none of the group × week interactions were statistically significant (ps > .30), indicating that the pattern of change in satisfaction over time did not differ significantly between groups.

Study Effort. On average, the control group reported a mean study effort of 4.37 (SD = 1.02) and the II group of 4.06 (SD = 1.16). Results of the mixed effect model indicated a significant main effect of group (β = −0.42, SE = 0.16, p = .007; 95% CI [-0.73;-0.12]), showing that participants in the II group reported lower levels of daily study effort compared to those in the control group. There was also a significant main effect of week 4, (β = 0.41, SE = 0.13, p = .001, 95% CI [0.17; 0.66]), indicating that effort was significantly higher in week 4 compared to week 1 across both groups. The interaction terms between group and week were not statistically significant (p > .18), suggesting that temporal changes in effort did not significantly differ between the groups.

Concentration & Distraction. The control group reported an average concentration of 3.74 (SD = 1.22), the II group of 3.71 (SD = 1.26). The main effect of group was not significant (β = −0.25, SE = 0.18, p = .156; 95% CI [-0.60; 0.09]), suggesting no difference in concentration between groups. Similarly, there were no significant main effects of week. However, a significant group × week interaction was observed in week 4 (β = 0.25, SE = 0.12, p = .042, 95% CI [0.02; 0.94]), indicating that participants in the II group reported higher levels of concentration in the final week compared to the control group. The interactions for weeks 2 and 3 were not significant. When investigating changes in distraction, the model revealed no significant main effect of group (β = 0.11, SE = 0.18, p = .55, 95% CI [-0.25; 0.47]), indicating no overall difference in distraction levels between groups. No significant main effects or interaction effects were found (all ps > .06) suggesting no changes in distraction over time or between groups.

Intrinsic & Extrinsic Motivation. The analysis of intrinsic motivation revealed no significant main effect of group (β = 0.24, SE = 0.21, p = .245, 95% CI [-0.17; 0.66]), indicating no overall difference in intrinsic motivation between groups. We found no significant main effects for week or interaction effects between group and week (all ps > .12), suggesting that intrinsic motivation remained stable across time and did not differ significantly between groups at any time point. The analysis of extrinsic motivation revealed a significant main effect of group (β = −0.58, SE = 0.23, p = .012, 95% CI [-1.02; -0.13]), indicating that the II group reported lower levels of extrinsic motivation compared to the control group. There were significant increases in extrinsic motivation over time, with main effects for week 3 (β = 0.62, SE = 0.11, p < .001, 95% CI [0.40; 0.84]) and week 4 (β = 1.46, SE = 0.14, p < .001, 95% CI [1.17;

1.74]) relative to week 1. We found no significant interaction effects between group and week (ps > .07).

Experiences ESM

Post-questionnaire responses indicated varied experiences with the daily prompts across groups. In the II group, reactions ranged from positive (n = 10), describing the prompts as helpful reminders that increased awareness and accountability, to neutral (n = 7), noting little influence on behavior. Fewer students reported negative experiences (n = 8), technical issues (n = 3), or emotional discomfort (n = 2), particularly when confronted with missed goals or unproductive days. Students in the control group generally responded positively (n = 26), describing the prompts as useful for daily self-reflection (n = 13) and appreciated their brevity and ease of completion (n = 8). Several students (n = 5) noted that prompts helped to increase awareness of study habits and motivated to follow planned learning activities. A smaller group (n = 4) reported neutral experiences, indicating little influence on behavior. Overall, students in the control group were more positive about prompts and perceived them as study or reflection reminder even if not all indicated direct behavioral changes.

Discussion

This study investigated the effect of implementation intentions on students' use of distributed practice (Aim 1) and explored students' daily study behavior over a four-week period within their authentic learning context using ESM (Aim 2). We first discuss differences across groups, then changes over time.

Group Differences in Distributed Practice

Despite the II group's formulation of implementation intentions, we did not find significant group differences in use of distributed practice. This suggests that formulating implementation intentions did not help students to use more distributed practice. Participants in both groups watched an introductory video explaining benefits of distributed practice and how to apply it during self-study. Additionally, participants in the II group formulated plans on how, when and where they wanted to incorporate regular reviewing sessions and how to overcome anticipated obstacles hindering them from goal-achievement. One possible explanation for the lack of group differences is that the daily measurement of study behavior or the information provided to both groups was sufficient to encourage the use of distributed practice. This aligns with research suggesting that mere measurement of behavior can alter it (e.g., French & Sutton, 2010; Godin et al., 2008) and providing information on effective learning strategies can influence study behavior, even without training (Ariel & Karpicke, 2018; McCabe, 2011). However, in both groups, overall use of distributed practice remained low, with participants engaging only on 1.61 days on average per week. This

low use could have weakened the intervention's potential impact, as students may generally lack necessary study or time-management skills to implement distributed practice effectively.

Furthermore, the format, quality, and internalizations of implementation intentions could explain the lack of effect. A recent meta-analysis by Sheeran et al. (2025) revealed that studies which followed an if-then format and where participants had a high motivation to pursue the goal had larger effect sizes than studies where this was not the case. In our study, we asked participants to specify 1) what and how they wanted to repeat previously learned content, 2) when, and 3) where they wanted to do so. This format supported participants to specify planned learning strategy, content, timing and location of review and thereby increase the quality and feasibility of specified action plans and preventing vague plans (e.g., If the lecture ends, then I will study). However, while most students successfully included key elements in their plans, they often struggled to specify these components in detail. This limited specificity could have weakened the cue-context link which is an essential part in implementation intentions (Gollwitzer, 1999; Sheeran et al., 2025) and aligns with previous findings suggesting that additional guidance may be necessary to support students in formulating specific and actionable strategies (Endres et al., 2021). Furthermore, it might take time for students to formulate and refine meaningful goals. As in previous studies (David et al., 2024), many students in our study reported the intention to start studying earlier. In the II group, this was supported by specifying a goal and a weekly opportunity to refine this goal to improve internalization and adjustment to participants' needs. It could be that goals only became realistic and useful after a few iterations, and the four-week course might have been too short to capture subsequent behavioral changes. Therefore, future research should measure students' goal-setting more long-term or include a follow-up research period to consider these refinement cycles.

Furthermore, most participants followed courses such as 'Critical Appraisal of Biomedical Publication', during which research articles were evaluated, or 'Introduction to Statistics', during which statistics were taught. These courses focus on practical skills with repeated practice embedded within course design. Thereby, this might have reduced participants' need to repeat content within self-study as it was incorporated within scheduled course hours.

Group Differences in Study Behavior

The daily learning strategies used suggest that participants in the II group incorporated more practice-testing in early course weeks and relied less on re-reading of literature than the control group. The daily study patterns revealed that the II group studied shorter, reported lower levels of daily study effort and extrinsic motivation and showed greater increase in concentration during the exam week compared to the control group.

This group difference could indicate more efficient study behavior in the II group,

as participants achieved comparable performance outcomes with less time investment. This could be because they started using more retrieval-based study strategies earlier in the course. These have been shown to enhance long-term retention more effectively than passive strategies such as re-reading (Roediger & Karpicke, 2006). Formulating implementation intentions might have contributed to this study efficiency by reducing mental effort required to initiate study sessions. By pre-establishing when, where, and how to study, students might have needed less effort when starting a study session as they had already planned what to do when (Lally et al., 2010; Lally et al., 2011). This could be especially important since students frequently indicate that they struggle to initiate study sessions (David et al., 2024). Similarly, the anticipation of obstacles and plans to overcome these could explain the II group's increased concentration during the exam week. Their obstacle plan might have helped to prioritize studying and not give in to distractions pointing towards a benefit of formulating implementation intentions. Further research is necessary to explore effects of implementation intentions on resource-management strategies such as time-management, distraction-management and mental effort.

Temporal Changes in Study Behavior

Next to differences in study behavior between groups, our results point to various changes over time. First, we found a significant positive effect of time on use of distributed practice, suggesting that participants in both groups used more distributed practice in weeks closer to the exam. Second, in both groups, students mainly used learning strategies such as summarization and re-reading. Closer to the exam, both groups incorporated more active learning strategies such as testing themselves and explaining content. Third, both groups reported more study effort, higher study satisfaction, more extrinsic motivation and studied longer in the weeks closer to the exam compared to the first course week. Intrinsic motivation and distraction did not differ significantly between groups, nor did they change meaningfully over time.

As mentioned above, the increased use of distributed practice over time might have been due to the active control group design or repeated measurement of our study which encouraged students in both groups to use more distributed practice. To disentangle a time from an intervention effect of information only, future research is necessary to investigate students' baseline engagement in distributed practice throughout a course without receiving information about distributed practice.

Furthermore, students in both groups used more distributed practice, incorporated more active learning strategies, studied longer, and experienced more pressure but also more study satisfaction closer to the exam, indicating that exam proximity influences study behavior. This aligns with research showing that assessment influences students' study behavior and motivation (e.g., Broekkamp & Van Hout-Wolters, 2007; David et al., 2024; Rovers et al., 2018). Additionally, the temporal changes in learning strategies suggest a level of metacognitive knowledge and regulation as students adapted their strategies to task demands, focusing on information organiza-

tion in the first weeks and memorization of content in later weeks. The increased study duration and experienced extrinsic motivation, study effort, and study satisfaction further underline the driving force of assessment in how students study. In the weeks closer to the exam, students in both groups indicated feeling more pressured to study, studying longer, but also investing more effort into their studying and being more satisfied with their studying. The opportunity cost model of effort (Kurzban et al., 2013) could explain why the perceived value of studying increases over time instead of being constant throughout the course. In first course weeks, studying is perceived as less urgent and rewarding, and therefore time spent studying feels even more costly than it inherently is. This is because time spent studying could be allocated doing more gratifying or less demanding activities, such as meeting friends, which is also supported by the anticipated obstacles students in the II group mentioned. Closer to exams, the urgency of studying increases its value and thereby decreasing the opportunity cost of studying, shifting students' cost-benefit analysis in favor of investing more time and effort into studying. This temporal shift supports the idea that students' motivation and study behavior are not static but responsive to contextual pressures and perceived utility.

Especially in undergraduate education, most students are assessed through multiple-choice exams, which emphasize recognition rather than recall of information (Epstein, 2007). Although distributed practice is well-established as beneficial for long-term retention (Carpenter et al., 2022; Cepeda et al., 2006), its value may not be recognized by students when their main goal is short-term performance to pass an exam that rewards performance rather than long-term understanding (David et al., 2024; Rea et al., 2022). In this case, short, intensive study sessions (i.e., cramming) can be more efficient for achieving the immediate goal of passing an exam (Rawson & Kintsch, 2005). This low perceived value is also supported by the low overall use of distributed practice in both groups. To support long-term learning, assessments should prioritize understanding and recall rather than recognition alone (Van der Vleuten et al., 2010).

Implications for Research and Practice

Overall, the temporal changes in study behaviors underline the dynamic and context-dependent nature of SRL and highlight the importance of using methodologies such as ESM to investigate these patterns. ESM enabled capturing temporal fluctuations in behavior and reflections within students' authentic learning context. The discrepancy between answers to the daily- and post-questionnaire highlights potential biases and inaccuracy in retrospective reporting, indicating another benefit of using ESM to capture study behavior (Breitwieser et al., 2024; Myin-Germeys & Kuppens, 2022). Furthermore, ESM seems to have a dual function by not merely measuring SRL but also helping students to reflect on their learning and thereby potentially enhancing learner's SRL. Previous studies suggest that prompting students to reflect on their study behavior through diary methods can be an intervention itself (e.g., Bre-

itwieser et al., 2024; McCardle & Hadwin, 2015). This is also suggested by participants' responses in the post-questionnaire, where both groups mentioned that they enjoyed filling in the daily prompts as it helped to reflect on studying. While our results suggest that students need support in formulating specific implementation intentions, there also appears to be a beneficial effect on increasing effective study behavior. Students in the II group studied shorter, used more retrieval-based learning strategies early in the course and performed similarly on the end-of-course-exam. Future research is necessary to disentangle effects of prompting frequent reflection and formulating implementation intentions.

ESM also presents itself as a unique tool supporting adaptive and personalized interventions accounting for students' individual, momentary needs (Biedermann et al., 2025; Breitwieser et al., 2024). Future research should aim to approach SRL using ESM with the goal to design more personalized and flexible tools that account for academic context, individual differences in for example ability, motivation, and readiness to change.

Furthermore, our results underline the importance of assessment in how students study. When assessments prioritize short-term performance over durable learning, students are incentivized to adopt performance-oriented strategies that optimize exam performance rather than promoting long-term learning and thereby use learning strategies that are most efficient for short-term goals(Scott, 2020). To promote long-term learning alignment between learning and assessment methods is necessary, which could be achieved by implementing programmatic assessments that spread out low-stakes evaluation moments over time (Van der Vleuten et al., 2010). This could reduce reliance on reactive studying and performance-orientation and foster a more consistent use of effective learning strategies (Van der Vleuten et al., 2010).

Limitations

The current study has several limitations. For example, we had a relatively heterogeneous sample that included students from various study years, programs, and courses. While increasing the generalizability of the findings, we could not account for how contextual factors, such as differences in course design or study years, influenced our findings due to the small number of participants per factor. However, since all courses followed a comparable structure within the same problem-based learning approach, the general learning environment was largely consistent across courses and thus within our sample. Also, while embedding the research in students' authentic learning context increased the ecological validity of this study, it limited our ability to account for confounding factors such as assignment deadlines, differences in study skills, or other concurrent interventions potentially influencing study behavior. Furthermore, although ESM minimizes recall biases as experiences are captured closer to their occurrence, it remains susceptible to social desirability and recall bias (Myin-Germeys & Kuppens, 2022). Future research could capture students' study behavior more frequently throughout the day to minimize delay between occurrence

and measurement of behavior. However, especially in SRL this is difficult without disrupting students' learning process. Instead, future research could consider triangulating ESM data with behavioral data such as log-data from learning platforms. Furthermore, we collected data for four weeks. As many students had weekly goals, this gave them only three to four opportunities to reach this goal depending on their starting point. Longer ESM periods would allow for greater variation in goal refinement and strategy use and could potentially offer insights into sustained behavioral changes. Therefore, future research should incorporate longer ESM periods or follow-up periods to explore potential delayed effects on strategy adoption or academic performance.

Conclusion

Our study suggests that implementation intentions did not increase the use of distributed practice. However, it seems that they might lead to more efficient study behavior such as using more retrieval-based strategies early in a course. Importantly, study behaviors changed over time in both groups with exam proximity as a key factor positively influencing students' use of effective learning strategies, study duration and evaluations such as investing more effort, experiencing more study satisfaction and more extrinsic motivation. This underlines the need to develop assessment methods that foster long-term learning. Furthermore, our study highlights the importance of investigating SRL over longer periods using ESM for exploring how university students adapt their study behavior to their learning contexts.

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Chapter 5

Investigating the Effects of Implementation Intentions on Distributed Practice in Higher Education Using a Longitudinal Experience-Sampling Design

An adapted version of this chapter has been submitted as:
David, L., Biwer, F., Crutzen, R., & De Bruin, A. (submitted). Investigating the effects of implementation intentions on distributed practice in higher education using a longitudinal experience-sampling design.

Abstract

Effective learning strategies such as distributed practice are crucial for academic success. Yet students often fail to apply them consistently and instead rely on habitual but less effective learning strategies such as summarizing. Helping students set goals in which they specify how they plan to incorporate effective learning strategies during their self-study may help build habits that include these effective strategies durably. Therefore, the present study examined whether goal-setting based on implementation intentions can promote students' use of distributed practice. Compared to the previous chapter, which examined a two-group intervention within one course, the present study extends this work using a three-group design and by exploring whether effects transfer to a later course through a follow-up ESM phase. In this study, first-year university students (N = 100; k = 1998 observations) were randomly assigned to one of three groups in which they had to either formulate implementation intentions for integrating distributed practice into self-study, received information about distributed practice only, or were in the control group. We tracked daily study behavior over four weeks using ESM, followed by a one-week ESM follow-up five weeks later to assess transfer effects. Contrary to expectations, implementation intentions did not increase use of distributed practice compared to the information-only or control group. Instead, students' initial intentions to use distributed practice predicted actual engagement. Across participants, strong temporal effects emerged. Closer to exams, use of distributed practice, study duration, effort, satisfaction, concentration, and extrinsic motivation increased, while distraction decreased. At follow-up, no group differences were observed, although students' earlier use of distributed practice predicted later use. The results underscore assessment demands as central to study behavior and reveal that translating study goals into consistent action remains challenging, particularly for complex, multi-step strategies such as distributed practice.

Keywords: Desirable Difficulties, Self-Regulated Learning, Higher Education, Experience Sampling Method, Goal-Setting

In higher education, students often struggle to use effective learning strategies. Instead of using strategies such as distributed practice or practice-testing, which are essential for academic outcomes (Bernardo et al., 2022; Dunlosky et al., 2013; Richardson et al., 2012), university students often rely on passive strategies such as re-reading, summarizing, and cramming study sessions shortly before exams (Blasiman et al., 2017; Hartwig & Dunlosky, 2012; Foerst et al., 2017; Rea et al., 2022). Students struggle to incorporate effective learning strategies consistently as these strategies feel more effortful, learning is not immediately evident, and students have habits of using ineffective learning strategies (De Bruin et al., 2023).

Although learning strategy training has been shown to effectively increase students' awareness and understanding of effective learning strategies, many students still struggle to translate this knowledge into their own study routines and fail to apply it consistently during their authentic learning contexts (Biwer et al., 2020; David et al., 2024). Furthermore, students seem to be more likely to use effective learning strategies at some times in their learning compared to others such as briefly before exams or when the task goal clearly highlights the utility of effective learning strategies (Abel et al., 2024; David et al., 2024). As consistent engagement in behavior is predicted by habits (Gardner, 2015; Rothman et al., 2009), it is crucial to support students in developing study habits that incorporate effective learning strategies and thereby support students' durable use of effective learning strategies (Fiorella, 2020). One approach that has been successful in supporting habit formation especially in the health domain is goal setting via implementation intentions (Sheeran et al., 2025). Implementation intentions are specific "if–then" plans that link a situational cue to a concrete behavior (Gollwitzer, 1999). If this situation-context cue is repeated often enough, a habit is formed and initiation of behavior becomes effortless and automatic (Lally et al., 2010; Verplanken, 2018).

Despite promising findings in other domains, evidence for the effectiveness of implementation intentions in supporting students' use of learning strategies in authentic educational settings remains limited (Endres et al., 2021; Hoch et al., 2023; Breitwieser et al., 2022). Previous studies have primarily examined short-term or isolated effects of implementation intentions, often outside students' authentic learning settings. The present study addresses this gap by investigating whether implementation intentions can promote consistent use of distributed practice across time and context by monitoring effects on students' study behavior over time and exploring transfer effects within a new context. To do so, in the current study, we tested whether implementation intentions can help students to incorporate regular review sessions within their self-study. For four weeks, we monitored daily goal achievement and study behavior. Furthermore, five weeks later, we administered a one-week follow-up period to explore potential transfer of effects to a new course.

Effective Learning in Higher Education

Effective learning in higher education requires students to engage in self-regulated learning (SRL), which describes the process of planning and setting goals, executing learning and monitoring progress, evaluating this process, and in response adapting behavior (Panadero, 2017; Zimmerman, 1986). A central aspect of effective SRL is the ability to select and use effective learning strategies (Zimmerman, 2002). Effective learning strategies often create 'desirable difficulties'; learning conditions during which learning feels effortful, yet this effort is conducive to learning (Bjork & Bjork, 2011). Examples of desirable difficulties are interleaving, practice-testing, or distributed practice. Incorporating these effective learning strategies within self-regulated learning is essential for long-term learning and academic achievement (Adesope et al., 2017; Dunlosky et al., 2013; Donker et al., 2014). However, even though they are more effective for long-term learning, students often rely on ineffective learning strategies such as summarizing and re-reading(Blasiman et al., 2017; Dunlosky et al., 2013). This is because desirable difficulties commonly require more effort, learning is not always immediately evident, and students have strong habits of using ineffective learning strategies that they developed in high school (De Bruin et al., 2023; Dirkx et al., 2019; Hui et al., 2021; Onan et al., 2022). Furthermore, effective learning strategies usually require more planning and thus better time-management skills than passive learning strategies. For example, when wanting to use practice testing, students need to account for additional time to search for or create testing materials. Similarly, when wanting to distribute their learning, students need to create a schedule and reserve time to allow for spacing out learning.

Students often struggle to overcome these difficulties associated with desirable difficulties and struggle to use them sustainably within their learning (Blasiman et al., 2017; Rea et al., 2022; David et al., 2024). The struggle to use effective learning strategies also changes over time and contexts. For example, students incorporate more practice testing in the weeks before an exam compared to the beginning of a course (David et al., 2024). Similarly, when task goals are clearer, students are more likely to engage in strategies such as interleaving, particularly when the perceived utility of the strategy is highlighted (Abel et al., 2024). These findings indicate that students' use of effective learning strategies fluctuates throughout learning instead of being consistent. This, in turn, also highlights the necessity of investigating SRL longitudinally to capture the influences of shifting motivation, task demands, and contextual cues.

Habit-Building Interventions in Learning Strategy Adoption

A wide range of interventions have been developed to enhance students' awareness and engagement with effective learning strategies (e.g., Ariel & Karpicke, 2018; Biwer et al., 2020; Broeren et al., 2023). Learning strategy training programs such as Study Smart have demonstrated effectiveness in increasing students' knowledge and use of effective learning strategies use, while also improving learning outcomes for

those with lower grades (Biwer et al., 2020; Biwer et al., 2023). Nevertheless, their influence on sustained behavioral change remains limited as many students struggle to consistently translate their knowledge to their authentic learning contexts (Biwer et al., 2020; David et al., 2024; Dignath & Veenman, 2021). Since habits are an important determinant of behavior (Verhoeven et al., 2012; Verplanken, 2018), they are widely recognized as central in maintaining behavioral change (Rothman et al., 2009; Verplanken, 2018). Thus, to ensure that students consistently apply effective learning strategies, it is essential to address the role of habits within self-regulated learning by integrating habit formation support to facilitate behavior maintenance (Fiorella, 2020). For instance, encouraging students to establish a study habit of creating and reviewing flashcards following each lecture may facilitate the formation of a study habit that integrates effective learning strategies and thereby gradually automates their use. Despite its potential, this perspective has received limited empirical attention, as most interventions concentrate primarily on enhancing knowledge rather than cultivating new study habits (Fiorella, 2020). We understand study habits as regularly repeated behaviors, such as the typical duration of study sessions, preferred learning strategies, or customary study times and settings (Lally et al., 2010). Habits are formed by repeatedly engaging in a specific behavior within a stable context (Lally et al., 2010). This repeated enactment builds strong associations between situational cues and behavioral responses (Gardner, 2015; Lally & Gardner, 2013; Lally et al., 2010; 2011). According to the goal–habit interface model (Wood & Rünger, 2016), habits often originate in goal-directed action. To initiate habit formation, an individual first sets a specific and measurable goal that provides motivational direction (Wood & Rünger, 2016), such as increasing the use of effective learning strategies. With repeated performance of the behavior in a stable context, cue–response associations strengthen (Lally et al., 2010). When contextual cues reliably trigger the behavior without deliberate intention, the habit becomes established, and enactment shifts from being goal-dependent to being directly cue-driven (Mazar & Wood, 2018). As goals are crucial for habit development, identifying goal-setting techniques that effectively translate intentions into repeated behavior is essential. One promising approach in this regard is the use of implementation intentions.

Implementation Intentions for Habit Formation

Implementation intentions are action plans that connect a situational cue with a behavioral response (Gollwitzer, 1999). They are usually formulated in an if-then format. For example, "If the lecture ends, I will review and update the notes I made during the lecture". Implementation intentions facilitate the transition from intentional, effortful behavior to automaticity by linking goal pursuit to contextual cues (Gollwitzer, 1999). By specifying when, where, and how the behavior should occur, abstract goals (e.g., use more effective learning strategies) are translated into concrete, context-specific plans (Gollwitzer, 1999). Goal setting thus plays a pivotal role in the early stages of habit formation, as it provides both the intentional and motivational

foundation necessary for initiating and repeating desired behaviors (Wood & Rünger, 2016). More specifically, implementation intentions help increase the likelihood of consistent enactment within stable contexts as abstract intentions are translated into concrete actions (Gollwitzer, 1999; Lally et al., 2010; Wood & Neal, 2007).

Thus, although habits eventually operate independently of conscious goals, the development of durable and effective study behavior seems to be supported by goal-directed processes during their initial formation (Wood & Rünger, 2016). A central advantage of such a habit-based approach for effective studying is that, once established, the use of effective learning strategies is triggered automatically by contextual cues rather than relying on momentary levels of motivation or effort (Bargh, 1994). In other words, forming habits may help students engage in effective learning strategies even when motivation is low or competing demands are high (Fiorella, 2020; Lally et al., 2011). To investigate whether implementation intentions actually stabilize students' use of effective strategies across motivational changes, it is essential to capture SRL longitudinally. This approach is particularly relevant because implementation intentions are designed to promote consistent behavior engagement over time by repeatedly linking goals to concrete situational cues.

In line with this, research in various domains indicates that implementation intentions are a useful tool in behavioral change (Sheeran et al., 2025). While there is evidence suggesting that they can be useful to increase desirable behavior in education (Hauser, 2018), such as increased study time (Clark et al., 2021), attendance (Duckworth et al., 2013), and vocabulary learning (Gollwitzer et al., 2011), there is limited research on whether they are effective in supporting the use of effective learning strategies in higher education. Endres et al. (2021) integrated the formulation of implementation intentions into a learning strategy training program designed to foster students' use of effective learning strategies. In Study 3, they tested whether students who formulated if–then plans reported greater knowledge of strategies and increased self-reported use of effective learning strategies compared to control groups. Students in the scaffolded implementation intention group and the prompting group reported higher use of effective strategies than students who formulated implementation intentions without scaffolding. However, in a follow-up study (Endres et al., 2021), they observed no effect of formulating implementation intentions on self-reported strategy use, which they largely attributed to the low quality of the implementation intentions students generated. While these findings indicate a potential effect of implementation intentions, especially when students are supported in formulating them, strategy use was measured only with a pre–post questionnaire, leaving it unclear whether the intervention led to consistent, durable changes in students' actual learning contexts. Breitwieser et al. (2022) similarly showed that prompting medical students to form implementation intentions during exam preparation improved exam performance, but these effects built up only during consecutive prompting days and diminished once prompts were withdrawn. In our own recent work (Authors, submitted), we tested whether implementation intentions could increase stu-

dents' use of distributed practice and monitored SRL daily across a four-week course using Experience Sampling Method (ESM; Csikszentmihalyi et al., 1977). This ESM implied that, for four weeks, university students were prompted daily to briefly report on whether they were able to include distributed practice, what kind of learning strategies they used, how long they studied, and how satisfied they were with their studying, how much effort they invested, how concentrated, distracted, intrinsically, and extrinsically motivated they were (Liborius et al., 2019). While implementation intentions did not increase distributed practice, students who formulated implementation intentions reported earlier adoption of effective strategies such as practice testing, shorter study durations, lower perceived effort, and increased concentration toward the end of the course, while performance on the end-of-course exam did not differ to students who merely received information about distributed practice. Across both groups, study behaviors fluctuated over time, with increases in strategy use, motivation, effort, and satisfaction closer to exams. Contrary to Breitwieser et al. (2022), we did not find that reminders influenced likelihood of following through with plans. A potential limitation of our previous study was that participants were not explicitly instructed to formulate their implementation intentions in the standard if–then format, which may have weakened their effectiveness. Consistent with a recent meta-analysis showing that if–then phrasing and strong goal commitment enhance intervention effects (Sheeran et al., 2025), students in our study often included the key components of an action plan but their formulations lacked detail.

Together, these studies yield mixed evidence on whether implementation intentions promote the use of effective learning strategies, potentially due to not following the specific if-then format or students' limited ability to formulate implementation intentions of sufficient quality. Building on this work, the present study aims to extend it by guiding students to create detailed if–then implementation intentions that link situational cues to concrete study actions. This way we aim to investigate whether implementation intentions can foster more consistent and durable use of distributed practice, using daily ESM to capture how students' self-regulated learning unfolds across an entire course and transfers to a subsequent course.

Using ESM, participants are repeatedly prompted, for example, via their smartphone to provide in-the-moment reports of their experiences and behavior within their natural contexts. ESM is commonly applied in health contexts as it allows for examining nuanced, within-person changes in experiences and behavior over time, which decreases recall bias and increases ecological validity (Myin-Germeys & Kuppens, 2021; Stadel et al., 2025; Velozo et al., 2024). Using ESM instead of commonly used pre- and post-questionnaires to assess students' SRL provides new insights into daily study behavior and learning strategy use during actual learning (Breitwieser et al., 2024). Therefore, in the current study, we applied ESM to monitor students' daily study behavior and examined whether formulation of implementation intentions supported use of distributed practice during students' SRL.

Current Study

To explore the effectiveness of a goal-setting approach to support students' use of effective learning strategies, we designed this study with a two-fold aim. First, we aimed to examine whether implementation intentions compared to information only versus a control group who received no information would help to increase students' use of distributed practice. We monitored students' use of distributed practice for four weeks and explored potential transfer effects five weeks later. Second, we aimed to monitor students' study behavior throughout one university course and explored temporal changes.

To investigate whether distributed practice can be increased via implementation intentions (use-of-distributed-practice hypothesis), participants were randomly assigned to one of three conditions. In the implementation intention (II) group, participants formulated intentions of how to incorporate regular review sessions within their self-study and formulated implementation intentions that could help them overcome an anticipated obstacle. Students in the information only group (IO), only received information about distributed practice and its benefits. The control group received no information. To monitor the use of distributed practice as well as other study behavior, we used ESM for four weeks with daily tracking of goal achievement and study behavior. We expected that participants in the II group would use increased distributed practice compared to both other groups. We conducted a one-week follow-up ESM period which was held five weeks later during a new course to explore whether effects persisted over time (transfer hypothesis). We explored whether participants in the II group would report a stronger intention to use distributed practice after the intervention (intention-to-use hypothesis) and whether they would achieve higher end-of-course exam grades, when controlling for baseline academic performance (performance hypothesis), compared to those in the IO and control group. Finally, we explored daily study behavior and how the intervention influenced these by exploring day-to-day fluctuations and group differences in study duration, effort, study satisfaction, concentration, distraction, intrinsic and extrinsic motivation.

This study extends prior work by testing implementation intentions for learning strategy use in an authentic educational setting and by examining both the development of study habits and their maintenance over time through daily monitoring and exploring potential transfer to a new course.

Method

This study was pre-registered on the Open Science Framework (OSF; https://osf.io/azb7n/overview?view_only=e077a9d5a466438c9c4e7ef8cbc55958). All data and study materials are available via the same link to OSF.

Participants

We conducted a four-week study with a follow-up period five weeks later using the Experience Sampling Method (ESM) during the 2024/25 academic year at the faculty of health, medicine and life sciences at a European university. Ethical approval was granted by the faculty's review board (FHML-REC/2024/134). We recruited first-year bachelor students through in-class announcements, posters, digital course platforms, and by invitation via course instructors, mentors and tutors. A total of 115 students signed up to participate in the study. Of these, 12 participants did not complete the full pre-questionnaire and therefore did not proceed to the intervention phase which was scheduled immediately after participants filled in the pre-questionnaire, resulting in 36 participants in the control, 38 in the IO, and 29 in the II group (see Figure 1 for an overview of the participants who completed each study phase). Three participants (two from the IO group and one from the control group) were excluded because they responded to fewer than 30% of the daily prompts. The final sample, therefore, comprised 29 participants in the II group, 36 in the IO group, and 35 in the control group. These participants were [85% female; 1% non-binary], mean age = 19.12, SD age = 1.3) first-year bachelor students studying Medicine (n = 47), Health Sciences (n = 24), Biomedical Sciences (n = 23), and Regenerative Medicine (n = 6) participated in this study. All students followed a four-week course which had an end-of-course exam scheduled at the end of week 4 of the first ESM period. The 1-week follow-up ESM period was scheduled five weeks later during which all students followed a new course.

Design and Procedure

Pre-Questionnaire

Information about the study and informed consent were conducted via Qualtrics. Then, participants downloaded the Avicenna Research App (Avicenna Research, 2024) which was used for all data collection. Participants first completed a pre-study questionnaire capturing demographic information (age, gender, and study program), academic performance (grades from their two most recent exams), and common study behavior at the beginning of a course and again for the end of a course (learning strategy use, study focus, study sessions, time spent studying, wishes for change of study behavior). After completing the pre-questionnaire, participants were randomly assigned to the implementation intention (II) group (n = 29), an information-only (IO) group (n = 36), or a control group (n = 35). In the II group, students watched a

video in which distributed practice was explained and they received some general advice on how to apply distributed practice within their self-study. Additionally, they were prompted to create a detailed implementation intention of incorporating regular review sessions within their self-study. Participants were asked to specify 1) what, 2) how, 3) when, and 4) where they planned to review. They were instructed to write the plan as an if-then statement in which they first specified when or where would signal them that it's time to start their review session, and then how and what they would do during that session. Furthermore, they had to formulate an if-then plan about how to overcome an obstacle that could potentially hinder them from achieving their reviewing goal (Clark et al 2021). In the IO group, participants only received information about distributed practice by watching the same video as in the II group. The control group received no further information about distributed practice. All groups were asked about their intentions to incorporate regular review sessions in the upcoming course (i.e. use distributed practice) using items from the Psychological Construct Repository (https://psycore.one/construct/?ucid=intention_73dnt604).

Daily Questionnaire (ESM)

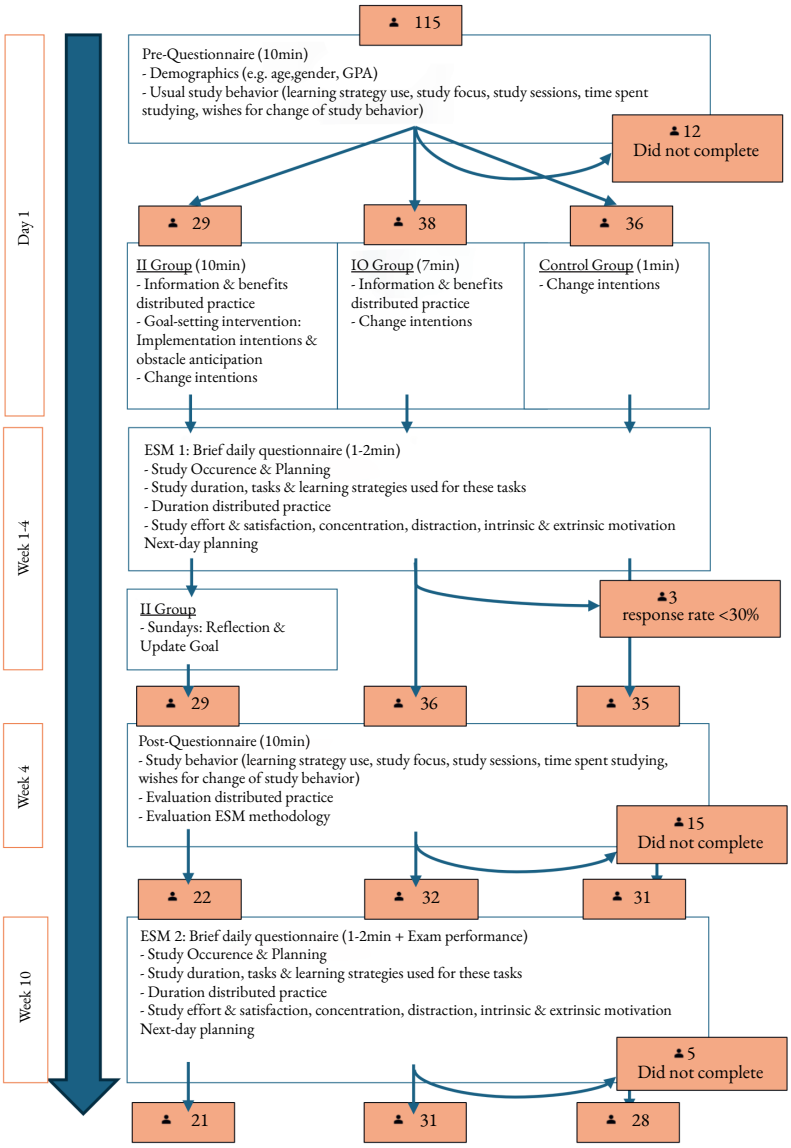
For the next four weeks, each evening at 18:00 participants received daily questionnaires tracking their study behaviors. The possibility to complete these daily questionnaires expired at 23:59 and in case students did not respond to the first prompt, they received reminders at 20:00 and 22:00. Questionnaire length depended on whether students studied that day or not and depending on study activity. If participants had studied that day, they were asked about their study duration, the tasks they worked on, which learning strategies they used for each of the tasks they worked on and if indicated that they reviewed, then they were asked how long they did so and whether they had planned to do this. Furthermore, participants who studied were asked to indicate their effort (Today, I made an effort when studying), concentration (Today, during my studying, I was very concentrated), distraction (Today, during my studying, I was very distracted), intrinsic motivation (Today, I was looking forward to my studying and dealing with its contents), extrinsic motivation (Today, I was driven to study mainly by the pressure I have) and satisfaction (I am very satisfied with the studying I have achieved today) (Liborious et al., 2019). All participants were asked whether they planned to study the next day and if so, they were asked about the tasks they planned to do. On Sundays, the II group had the opportunity to reflect on and update their implementation intentions and obstacle plan. The ESM period lasted 15–26 days depending on participants' individual start date and was embedded within the duration of one four-week long university course. All courses had an end-of-course exam scheduled in week 4 of the ESM period.

Post- Questionnaire and Follow-Up ESM Period

At the end of the ESM period, participants completed a post-questionnaire assessing their study behavior for the last weeks of the course using the same questions

used in the pre-questionnaire. They also evaluated their experiences using distributed practice and the ESM methodology. Five weeks later, we administered a follow-up ESM period. For five days, participants completed the daily questionnaire again. On the last day, participants also reported their exam grade they received for the course taught during the main ESM period. Our overall study procedure and design can be found in Figure 1.

Figure 1. Study procedure and design



Analysis

The final dataset of the main ESM period included k = 1998 daily responses from n = 100 participants of which k = 1441 represented study occurrences. Furthermore, we collected k = 343 observations during the follow-up dataset from n = 80 participants, of which k = 213 represented study occurrences. A Kruskal–Wallis test indicated no significant differences in response rates between groups, $\chi^2(2) = 1.08$, p = .58, with responses to the daily questionnaire during the main ESM period averaging 86% (18.8%) in the II group, 84.8% (SD = 23.6%) in the IO group, and 91.6% (SD = 12.6%) in the control group. For our use of distributed-practice hypothesis, ESM data were aggregated weekly to generate a primary outcome variable: the number of days per week a participant used distributed practice (range: 0–7). We conducted a mixed-effects regression using the lme4 package in R (Bates et al., 2015). The dependent variable was the weekly cumulative use of distributed practice. Fixed effects included experimental group (three levels) and week, with random intercepts for participants:

distributedPractice_cumulative ~ group * week + (1 | participant_id). To examine our transfer hypothesis, we ran a linear regression model on participants' cumulative use of distributed practice across the 5-day follow-up period, controlling for their mean weekly distributed practice across the four weeks main ESM period. For our intention-to-use hypothesis, we added participants' intention-to-change score as a fixed effect to the primary mixed-effects model to examine whether stronger intentions predicted greater engagement in distributed practice. To examine our performance hypothesis, we conducted a linear regression model with post-exam score as the dependent variable and experimental group as the predictor, controlling for baseline academic performance by averaging the two prior exam scores.

For group and time differences in daily study behaviors such as study duration, study satisfaction, study effort, concentration, distraction, intrinsic and extrinsic motivation, we applied mixed-effects models with the respective variable as the dependent variable. Each model included group, time (week), and their interaction as fixed effects, and participant as a random intercept. To explore the transfer effects of our intervention, we analyzed data from the one-week follow-up ESM period using the same approach. For each daily study behavior (e.g., study duration, study effort, concentration), we included experimental group as fixed effect, with a random intercept for participant.

Open-ended responses from the post-questionnaire and implementation intention and obstacle plan prompts were analyzed qualitatively using thematic coding. Following an initial review of the material, responses were organized into thematic clusters and summarized by content. In line with the approach described by Endres et al. (2021), the quality of implementation intentions was evaluated using a 10-point scoring system: one point each was awarded if the plan mentioned a review session and another if they were structured according an "if-then" format. The remaining eight points were based on the specificity of four key elements: how, what, when, and

where the review would take place. Each of these elements were rated separately for (a) inclusion (0 or 1 point) and (b) concreteness (0 or 1 point). Obstacle-related plans were similarly coded, receiving one point for naming an obstacle, another for providing a strategy to address it, another point, if this was formulated in an "if-then" form, and further points for the specificity of both elements (0 for vague, 1 for specific), producing a maximum possible score of 5.

Results

Sample Characteristics and Descriptive Analyses

Descriptive statistics for age, gender, study program, and baseline academic performance as operationalized by the previous two course grades are summarized in Table 1. A nonparametric Kruskal–Wallis test indicated no significant differences in age between groups, $\chi^2(2) = 1.94$, $p = .38$. Fisher's exact tests indicated that the groups did not differ significantly in terms of study program ($p = .32$) or gender distribution ($p = .71$). Exam scores of the previous two courses were combined to generate a baseline academic performance. Results of an ANOVA showed no significant differences between groups for academic performance prior to the study ($F(2, 97) = 0.11$, $p = .90$). This indicates that groups were comparable in demographic composition and prior academic achievement. In the II group, participants responded on average to 21.8 daily prompts (SD = 3.57), in the IO group to 20.6 prompts (SD = 4.92), and in the control group to 23.1 (SD = 2.98). A one-way ANOVA was conducted to examine differences in exposure duration (number of response days) across groups. There was a significant effect of group on exposure days, $F(2, 97) = 3.51$, $p = .034$.

Table 1. Descriptive Statistics Per Group

Variable	II (n=29)	IO (n=36)	Control (n=35)
Age (M ± SD)	19.3 ± 1.23	19.1 ± 1.27	19 ± 1.41
Gender, n (%)			
Female	24 (82.8%)	30 (83.3%)	31 (88.6%)
Male	4 (13.8%)	6 (16.7%)	4 (11.4%)
Non-binary	1 (3.4%)	-	-
Study program, n(%)			
Biomedical Sciences	8 (27.6%)	7 (19.4%)	8 (22.9%)
Health Sciences	5 (17.2%)	9 (25.0%)	10 (28.6%)
Medicine	15 (51.7%)	15 (41.7%)	17 (48.6%)
Regenerative Medicine	1 (3.4%)	5 (13.9%)	-

Variable	II (n=29)	IO (n=36)	Control (n=35)
Baseline Academic Performance (M ± SD; range 1-10)	6.80 ± 0.93	6.78 ± 1.01	6.88 ± 0.78

Note. Values represent n and percentage per group for the variables gender and study program and means and standard deviations for age and baseline academic performance.

Goal and Obstacle Plans

Participants in the II group formulated if-then plans of when and where they wanted to incorporate regular reviewing sessions, how and what they wanted to review and formulate an if-then plan to overcome an obstacle that could hinder them from achieving their regular reviewing. Most goals focused on reviewing course content using learning strategies such as practice testing, re-reading, summarization, or visualization, while a smaller number (k = 3) targeted initiating study sessions. Mean goal quality scores were 7.1 (SD = 1.95). Mean obstacle quality was 4.65 (SD = 0.77). Obstacles students mentioned were forgetting (k = 11) and lack of motivation (k = 9), followed by distraction from the phone (k = 3), poor planning (k = 3), and other reasons (k = 3). To overcome these obstacles, participants most often reported strategies such as setting reminders (k = 9) or improving their planning routines (k = 5), with a smaller number mentioning removing distractions (k = 3), rescheduling study sessions (k = 2), or using self-reward strategies (k = 2).

Each week, participants in the II group indicated whether they had achieved their study goal and, if not, the reasons for non-achievement. The percentage of participants reporting goal achievement increased steadily across the four-week intervention period, from 32% in Week 1 to 38% in Week 2, 54% in Week 3, and 62% in Week 4. This suggests growing engagement and achievement in implementing their intended reviewing sessions over time. Most common reasons for not achieving goals were lack of time (k = 13), low motivation (k = 10), and forgetting (k = 9). Less common reasons included lack of commitment (k = 4), feeling overwhelmed (k = 3), and insecurity about study steps (k = 2).

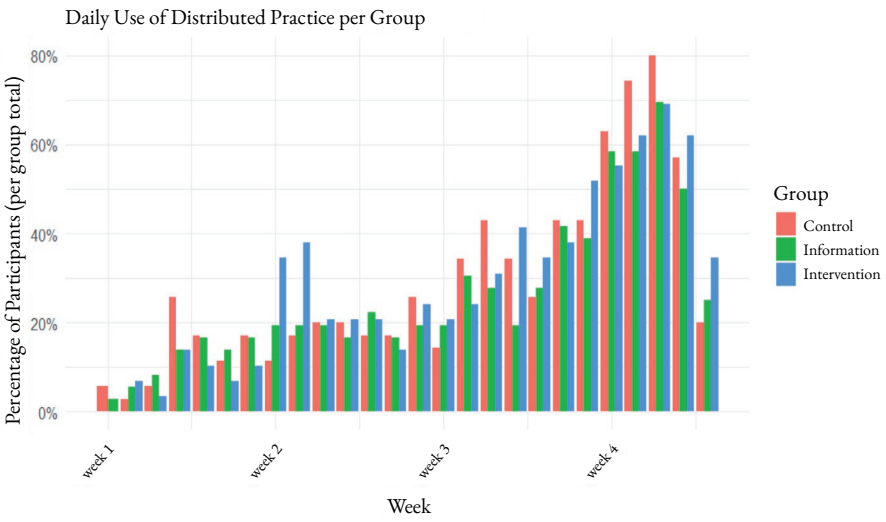
Research Aim 1: Use of Distributed Practice

Use-of-distributed-practice hypothesis

The daily use of distributed practice per group is visualized in Figure 2. There is a significant main effect of week, indicating that distributed practice increased over time. Specifically, compared to Week 1, participants reported significantly higher daily distributed practice in Week 3 (b = 1.37, 95% CI [0.66; 2.07], SE = 0.36, t(272) = 3.83, p < .001) and Week 4 (b = 1.99, 95% CI [1.30; 2.70], SE = 0.36, t(272) = 5.58, p < .001), while Week 2 did not differ significantly from Week 1 (b = 0.28, 95% CI [-0.42; 0.98], SE = 0.36, t(272) = 0.79, p = .43). There was no significant main effect

of group, all ps > .56 (information-only vs. control: b = 0.09, 95% CI [-0.79; 0.97], SE = 0.45, t(329) = 0.20, p = .84; implementation intention vs. control: b = –0.27, 95% CI [-1.18; 0.64], SE = 0.47, t(325) = –0.58, p = .56). The group × week interactions were not significant (all ps > .21), suggesting that the observed increase in distributed practice across the four weeks was comparable across all three groups. To account for the significant differences in exposure days between groups, we ran a linear mixed-effects model with group, week, and exposure duration on weekly distributed practice use. Similar to the main model, the model indicated more use of distributed practice in Week 3 (b = 1.35, 95% CI [0.65; 2.06], SE = 0.36, p < .001) and Week 4 (b = 1.98, 95% CI [1.29; 2.69], SE = 0.36, p < .001) compared to Week 1 but no significant main effects of group or exposure duration, and no significant group × week interaction, ps > .21.

Figure 2. Daily Use Distributed Practice Per Group during the Main Period



Transfer-hypothesis

During the follow-up period, participants in the II group used distributed practice on 1.68 days on average (SD = 2.12), the IO group on 1.94 days (SD = 2.21), and the control group on 0.93 days (SD = 1.60). The overall model in which we examined group differences in participants' use of distributed practice during the follow-up period indicated no significant main effect of group ($b_{(IO)}$ = 0.40, 95% CI [–0.07, 0.88], p = .095; $b_{(II)}$ = 0.20, 95% CI [–0.30, 0.69], p = .44). Baseline weekly distributed practice during the main ESM period was a significant positive predictor of follow-up engagement (b = 0.24, 95% CI [0.07, 0.41], p = .005), suggesting that students who used distributed practice more frequently during the main ESM period were also more likely to continue doing so during the follow-up period.

Intention to Use Hypothesis

Participants' mean intention to use distributed practice were M = 3.14 (SD = 0.55) in the II group, M = 2.83 (SD = 0.90) in the IO group, and M = 2.77 (SD = 0.84) in the control group. An ANOVA indicated that these differences were not statistically significant, $F(2, 97) = 1.94$, $p = .149$, suggesting that groups did not differ in their intention to use distributed practice. The multilevel model revealed that intention-to-use distributed practice was a significant positive predictor of actual use of distributed practice, $b = 0.64$, 95% CI [0.18; 0.74], SE = 0.22, $p = .004$. This indicates that participants who reported stronger intentions to use distributed practice engaged more frequently in distributed practice, independent of group assignment.

Performance Hypothesis

Students performed similarly across groups on the end-of-course exam (control: M = 7.16, SD = 1.30; information-only: M = 7.61, SD = 1.20; implementation intention: M = 7.30, SD = 0.90). An ANOVA suggested that these differences were not statistically significant ($F(2, 65) = 0.98$, $p = .38$). The linear regression suggested baseline academic performance as significant predictor for end-of-course exam, $b = 0.61$, 95% CI [0.28; 0.94], SE = 0.17, $t(64) = 3.70$, $p < .001$, indicating that students with higher prior performance achieved higher post-exam scores. After controlling for baseline performance, there were no significant group differences in post-exam scores: IO vs. control, $b = 0.37$, 95% CI [-0.23; 0.97], $p = .22$; II vs. control, $b = 0.26$, 95% CI [-0.44; 0.95], $p = .46$, suggesting that implementation intentions did not result in higher end-of-course exam results.

Research Aim 2: Daily Study Behaviors

Individual linear mixed-effects models were conducted to examine changes in students' daily study behaviors across the four-week course period as a function of group. Across all variables we did not find significant main effects of group and for most variables we also did not find significant group × week interactions (all ps > .10), indicating that overall temporal patterns were comparable across groups. However, we found several significant main effects of week, reflecting temporal changes in study behavior throughout the course. Study duration increased substantially from Week 1 to Week 4 ($b = 121.30$, 95% CI [82.77; 134.00], SE = 13.07, $t(1357) = 8.29$, $p < .001$). Similarly, time spent on distributed practice rose in the final week ($b = 123.09$, 95% CI [76.88; 170.92], SE = 23.99, $t(629) = 5.16$, $p < .001$) in all groups.

We found significant main effects for week 4 compared to week 1 for study satisfaction ($b = 0.58$, 95% CI [0.29; 0.88], SE = 0.15, $t(1362) = 3.85$, $p < .001$), study effort ($b = 0.47$, 95% CI [0.20; 0.74], SE = 0.14, $t(1355) = 3.43$, $p < .001$), concentration ($b = 0.56$, 95% CI [0.27; 0.85], SE = 0.15, $t(1363) = 3.75$, $p < .001$). We found a significant main effect for week 3 ($b = 0.41$, 95% CI [0.13; 0.69], SE = 0.14, $t(1366) = 2.91$, $p = .004$) and week 4 ($b = 1.02$, 95% CI [0.72; 1.31], SE = 0.15, $t(1353) = 6.77$, $p < .001$) in extrinsic motivation. While intrinsic motivation remained stable (ps > .10),

the results suggest increased study behavior and concentration toward the end of the course.

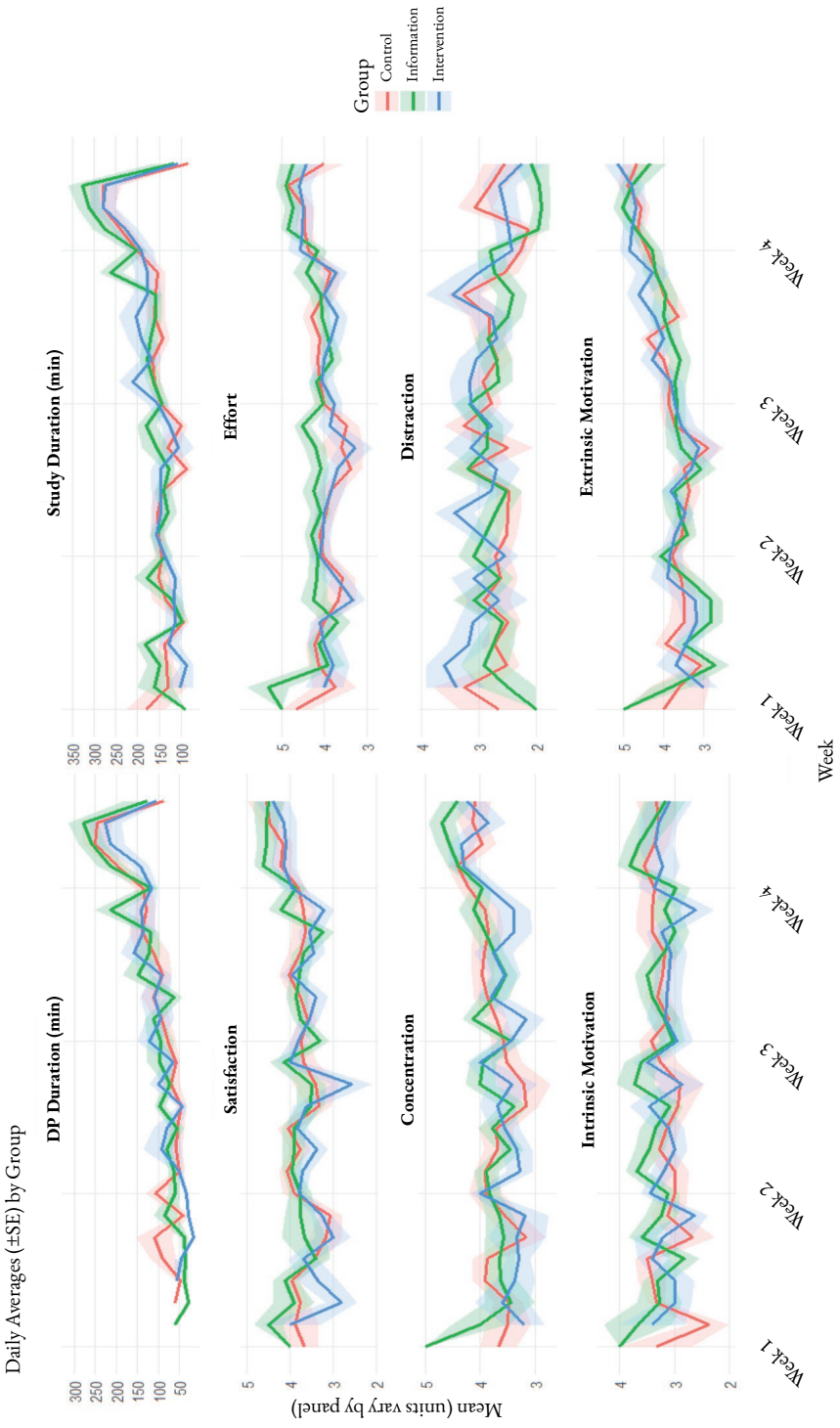
We found a significant group × week interaction for distraction, b = −0.52, 95% CI [-1.02; -0.03], SE = 0.25, t(1378) = −2.08, p = .038, indicating that students in the II group reported reduced distraction in the final course week compared to the control group. Also, participants in the IO group reported significantly lower distraction in Week 4 compared to the control group (b = −0.49, 95% CI [-1.00; -0.10], SE = 0.20, t(1378) = −2.40, p = .017). A visualization of the study behavior can be found in Figure 3.

Transfer Effects: Daily Study Behavior

When investigating transfer effects of the intervention to the daily study behavior during the one week follow-up ESM period five weeks later, we found no difference between groups in daily study duration ($b_{(IO)}$ = −17.04, 95% CI [-54.20; 20.12], SE = 18.96, t(73.16) = −0.90, p = .372; $b_{(II)}$ = 32.72, 95% CI [-9.31; 74.75], SE = 21.44, t(75.20) = 1.53, p = .131). There was also no difference in time spent on distributed practice ($b_{(IO)}$ = −18.59, 95% CI [-70.22; 33.05], SE = 26.35, p = .486; $b_{(II)}$ = 5.32, 95% CI [-51.78; 62.42], SE = 29.13, p = .856). Likewise, for effort, there was no difference between groups ($b_{(IO)}$ = −0.23, 95% CI [-0.56; 0.09], SE = 0.16, p = .160; $b_{(II)}$ = 0.01, 95% CI [-0.35; 0.38], SE = 0.19, p = .949).

However, there was a significant difference in study satisfaction, with the IO group reporting lower satisfaction than the control group (b = −0.47, 95% CI [-0.85; -0.09], SE = 0.19, t(57.90) = −2.46, p = .017). No difference was observed for the II group (p = .263). A similar pattern emerged for concentration, where the IO group reported lower concentration compared to control group (b = −0.44, 95% CI [-0.84; -0.05], SE = 0.20, t(64.58) = −2.19, p = .032), while the II group again did not differ (p = .821). No significant differences were found for distraction ($b_{(IO)}$ = 0.36, 95% CI [-0.06; 0.79], SE = 0.22, p = .100; $b_{(II)}$ = 0.16, 95% CI [-0.33; 0.64], SE = 0.25, p = .533), intrinsic motivation ($b_{(IO)}$ = −0.28, 95% CI [-0.80; 0.24], SE = 0.27, p = .293; $b_{(II)}$ = 0.27, 95% CI [-0.32; 0.86], SE = 0.30, p = .373), or extrinsic motivation ($b_{(II)}$ = 0.22, 95% CI [-0.16; 1.19], SE = 0.30, p = .478; $b_{(IO)}$ = 0.51, 95% CI [-0.38; 0.81], SE = 0.34, p = .138).

Figure 3. Daily mean levels of study behaviors and motivational variables across the course per group.


Daily Averages (±SE) by Group
DP Duration (min)
Study Duration (min)
Satisfaction
Effort
Concentration
Distraction
Intrinsic Motivation
Extrinsic Motivation
Mean (units vary by panel)
Week
Week 1
Week 2
Week 3
Week 4
Group
Control
Information
Intervention

Note. The figure displays the daily mean scores (± standard error) for study-related variables across the four-week main study period, separately for each group (Control, Information-Only, and Implementation Intention). Panels include distributed practice duration (minutes), total study duration (minutes), and Likert-scale ratings (1–6) for effort, satisfaction, concentration, distraction, intrinsic motivation, and extrinsic motivation. At the end of week 4 all participants had an end-of-course exam.

Learning Strategies

We summarized the most commonly used learning strategies used for distributed practice per group, per week during the main and follow-up ESM period in Table 2. Across all groups, students heavily relied on summarizing, re-reading notes, and watching videos to review previously learned content. In week 4, students from all groups used more practice testing during their distributed practice.

Table 2. Learning Strategies Used For Distributed Practice Per Week Per Group

Group	Week	Most Common Strategy	Second Most Common Strategy	Third Most Common Strategy
II Group	1	Summarizing	Re-reading literature	Watching videos
	2	Summarizing	Re-reading notes	Watching videos
	3	Summarizing	Re-reading notes	Re-reading literature
	4	Re-reading notes	Practice testing	Summarizing
	10	Re-reading literature	Re-reading notes	Summarizing
IO Group	1	Summarizing	Watching videos	Re-reading notes
	2	Summarizing	Re-reading notes	Watching videos
	3	Summarizing	Re-reading literature	Watching videos
	4	Practice testing	Re-reading notes	Summarizing
	10	Summarizing	Re-reading literature	Re-reading notes
Control Group	1	Summarizing	Re-reading notes	Re-reading literature
	2	Summarizing	Re-reading notes	Watching videos
	3	Summarizing	Re-reading notes	Watching videos
	4	Re-reading notes	Practice testing	Summarizing
	10	Summarizing	Explaining content	Highlighting

Discussion

This study examined whether implementation intentions enhance students' use of distributed practice and influence related study behavior in university students' authentic learning contexts. Contrary to our use-of-distributed-practice hypothesis, there were no significant differences between the implementation intention (II), information-only (IO), and control groups in use of distributed practice or relat-

ed study behavior. Instead, students' intentions to use distributed practice positively predicted actual engagement in distributed practice independent of group (intention-to -use hypothesis). Furthermore, strong time effects indicated that distributed practice, study duration, effort, satisfaction, concentration, and extrinsic motivation all increased as exams approached, whereas distraction decreased and intrinsic motivation remained stable (daily study behavior). These temporal dynamics suggest that changes in students' learning behavior were primarily driven by contextual and temporal factors, particularly exam proximity, rather than by the implementation intentions intervention. An interaction effect indicated that both the IO and II group reported lower distraction levels toward the end of the course compared to the control group. These differences did not persist in the follow-up period, during a new course, five weeks later. Contrary to our exploratory transfer hypothesis, at follow-up, participants across groups showed comparable levels of distributed practice, which were predicted by mean use of distributed practice during the main ESM period. Also, across groups, there were no significant differences in study duration, effort, distraction, intrinsic and extrinsic motivation, with the exception that the IO group reported lower levels of satisfaction and concentration compared to the control group.

Implementation Intentions and Study Behavior

Overall, formulating implementation intentions did not lead to an increased use of distributed practice, either in the short or long term. Although participants in the II group were guided to specify when, where, and how they would engage in distributed practice, these plans did not translate into higher actual use. Instead, the strength of students' self-reported intentions to use distributed practice predicted actual engagement. Across groups, students expressed comparable intentions to incorporate distributed practice, similar to findings from Endres et al. (2021). This suggests that merely providing information or prompting to formulate implementation intentions did not substantially alter intention to act or heighten motivation to incorporate it. This lack of motivation could be one of the factors explaining the lack of effectiveness of implementation intentions, as motivation to pursue the formulated goal is an important predictor for the effectiveness of implementation intentions (Sheeran et al., 2025).

Furthermore, previous research suggests that students require more guidance or scaffolding to formulate high-quality, specific implementation intentions (Endres et al., 2021). Also in the current study, the quality of implementation intentions may have limited their effectiveness. While many plans were specific and situationally bound, the feasibility or realism of these cues may have been low. While students had an example and were asked to formulate the implementation intention in an if-then format, they received no feedback on their specified goal. Without feedback on goal realism, self-set goals might have been too high, or situational cues might not have triggered the intended behavior because the situational cues or behavioral response were unrealistic and therefore reducing the likelihood that specific situational cues

would automatically trigger the intended behavior (Prestwich & Kellar, 2014). Future research could provide immediate, personalized feedback to improve goal quality, even though assessing feasibility requires contextual knowledge about background and ability of learner which can be difficult to standardize. So far, there is no consensus on how to best assess the quality of implementation intentions in educational settings.

To mitigate this lack of feedback, students had the opportunity to revise goals weekly and reflect on reasons for not achieving their goal. Although distributed practice increased over time, similar temporal trends in the IO and control group suggest that this rise reflected exam proximity rather than improved goal quality. The weekly goal and obstacle reflections may have fostered awareness rather than execution as students could identify barriers (e.g., lack of time or motivation) but struggled to convert these insights into concrete behavioral adjustments. Thus, reflection may have supported metacognitive monitoring without producing actionable regulation. This is supported by other SRL research which suggest that students struggle to make accurate judgements about their learning and adapt subsequent behavior accordingly (Binbasaran Tuysuzoglu & Greene, 2015; Raković et al., 2022; Pardo et al., 2019).

Complexity of Distributed Practice

Another reason that could explain the lack of effect of implementation intentions on use of distributed practice is that distributed practice itself represents a complex, multi-step learning strategy that requires planning, retrieval, and scheduling over extended periods. Recent research suggests that complex behaviors are inherently more difficult to automate than single, discrete actions (Phillips & Mullan, 2023), such as "take medication after breakfast". Even with repeated reflection, students may have struggled to integrate distributed practice into their routines amid competing demands such as working on assignments, having to work, or social obligations. Consequently, the combination of potentially unrealistic implementation intentions, limited scaffolding, and the inherent complexity of distributed practice may explain why the intervention did not translate into greater behavioral engagement compared to the control groups. Future interventions might benefit from initially targeting the instigation habit of consistent studying rather than incorporating effective learning strategies immediately (Phillips & Gardner, 2016). By for example forming a plan such as "When the lecture ends, I will go to the library" students will be supported in starting to study more consistently. By focusing on easier-to-implement triggers, regular study sessions are initiated, and these can later be extended to include effective yet effortful learning strategies (Mullan & Novoradovskaya, 2018; Phillips & Mullan, 2023; Sylvester et al., 2016).

Assessment Pressure as Driver for Learning

The time effects observed across variables underscore the central role of assessment

pressure as a powerful regulator of students' study behavior. Distributed practice, study duration, duration of distributed practice, effort, satisfaction, concentration, and extrinsic motivation increased, while distraction decreased as exams approached. This is consistent with prior research showing that learning peaks when academic stakes are most salient (Blasiman et al., 2017; David et al., 2024; Rea et al., 2022; Rovers et al., 2018). The absence of group differences in motivational and affective indicators further indicates that the implementation-intention intervention did not buffer against motivational decline over time. This pattern likely reflects that motivation and satisfaction are more sensitive to situational pressures than to brief self-regulatory interventions while still being essential to support learners in sustaining behavioral change (Sheeran et al., 2025). Additionally, changes in students' strategy use over time reflect a focus on selecting and organizing information in the initial weeks by summarizing and re-reading and memorizing material closer to the exam period using retrieval-based strategies. Moreover, participants most frequently cited lack of time and motivation as reasons for not achieving their goals, reinforcing the idea that while students may understand what effective strategies such as distributed practice entail, they struggle to prioritize them early in the semester when exam pressure is low (David et al., 2024). Collectively, these findings highlight the importance of examining self-regulated learning longitudinally and in authentic educational contexts, where external demands and assessment structures exert a substantial influence on students' self-regulated learning.

Transfer Effects

During the follow-up ESM period, students in the IO group reported lower satisfaction and concentration than the control group. Given that this was one significant result among largely non-significant group differences, the effect should be interpreted cautiously and could potentially indicate that participants in the IO group were made aware of effective strategies but not supported in using them. This could have potentially created a gap between knowledge and action that undermined their study satisfaction and ability to concentrate. Furthermore, findings indicate that participants' prior engagement in distributed practice during the main ESM period predicted their subsequent use of the strategy during the new course, whereas group assignment did not. This pattern suggests that sustained engagement in distributed practice may depend less on external instruction or goal setting but rather on habitual use of the learning strategy. This is in line with other research suggesting that habits are an important predictor in behavioral maintenance (Gardner, 2015; Rothman, 2009; Verplanken, 2018).

Furthermore, the fact that prior use of distributed practice predicted later use could highlight the importance of having to experience the benefits of distributed practice to foster consistent use. It might be that once students have successfully engaged in distributed practice during their learning and experience it benefits such as increased retention, and reduced workload and stress during the exam period, they are

more likely to continue applying it in a next course. Interventions may need to focus on helping students "get started" and persist long enough for automaticity to develop (De Bruin et al., 2023; Onan et al., 2022).

Taken together, these findings suggest that implementation intentions alone may be insufficient to initiate complex behaviors like distributed practice. Instead, once students begin to engage, repeated performance may itself serve as critical factor of transfer and habit consolidation. Future research should therefore address the question of how to support students in starting and sustaining effective learning behaviors early on in a course through environmental cues and structured prompts, which may promote durable changes in self-regulated study habits (De Bruin et al., 2023; Fiorella, 2020).

Strengths and Limitations

A strength of the current study is its ecological validity and longitudinal design. By collecting data via ESM, we were able to collect rich, situational data on students' daily study behavior, revealing how their use of learning strategies, study duration, effort, and motivation fluctuated across time and courses. Although the expected intervention effects were not found, the study offered a uniquely detailed understanding of students' authentic learning processes over time. This further highlights the importance of researching self-regulated learning longitudinally within students' authentic learning. Nevertheless, several limitations need to be considered.

First, the sample was drawn from four first-year courses with similar structures, which enhances generalizability. While there were no significant differences in study programs in terms of group composition, this variability in courses could have potentially introduced additional noise and thereby limited the detectability of effects. At the same time, this variability in courses also represents a strength of the study. It allowed us to capture students' learning behavior across various courses and therefore yields a more realistic understanding of how students regulate their learning across different course structures and demands

Second, while common in educational research and when using ESM, we relied on self-report measures. This could have potentially limited measurement precision, though frequent sampling mitigated recall bias. Future work should therefore combine ESM with trace or log data from learning platforms for even more objective indicators of study behavior (Greene et al., 2021; Velozo et al., 2024).

Third, the four-week intervention period may have been too short for habit consolidation. The latter typically requires repeated reinforcement over stable contexts (Lally et al., 2010). Extending the intervention and adding periodic reminders or reflection prompts could strengthen effects, though overreliance on external cues should be avoided to preserve autonomy (Nobbe et al., 2024). Moreover, there was some variation in participants' exposure duration to the intervention due to staggered starting dates of the experience sampling period. Allowing for flexible entry dates enabled the inclusion of a larger sample, but it also resulted in differences in the number

of days participants were exposed to the intervention. To account for this, we included exposure days as a covariate in our model to examine whether the length of participation influenced the use of distributed practice. The results indicated that exposure duration did not significantly affect distributed practice behavior. Nevertheless, future studies should aim to minimize variability in starting times to ensure more consistent exposure across participants and to strengthen internal validity.

Additionally, in line with the scope of the present research questions, we examined group-level differences. In addition to differences between groups, prior research suggests that the effectiveness of learning activities can depend strongly on learners' individual engagement and motivation (Biedermann et al., 2025). Therefore, future work should examine how individual characteristics and daily patterns influence the effectiveness of implementation intentions. It is possible that students who already possess higher levels of self-regulatory competence or intrinsic motivation are better able to translate implementation intentions into concrete behavior, whereas students with lower self-regulatory capacity may require more structured scaffolding or external prompts to benefit. Or that depending on temporal fluctuations in motivation or willingness to invest effort, students might be more willing to work on their goal. Investigating these moderating factors could provide valuable insights into for whom and under what conditions interventions are most effective, thereby informing the design of more personalized and adaptive support systems (Breitwieser et al., 2024).

Conclusion

The current study suggests that implementation intentions did not increase the use of distributed practice. Instead, students' intentions to use distributed practice predicted actual engagement, and transfer to a next course was predicted by use of distributed practice during the main study period. This suggests that intention to use and habitual use are more important predictors of behavior enactment rather than goal setting. These findings indicate that while students can articulate when and how they intend to study, translating such plans into sustained behavior change remains challenging, particularly for complex, multi-step strategies like distributed practice. At the same time, the study highlights that self-regulated learning behaviors are strongly shaped by contextual factors, such as exam proximity. Future interventions might benefit from first supporting students in initiating consistent studying and in a second step add effective learning strategies to this consistent study behavior to better support students in developing durable, self-regulated study routines that extend beyond a single course.

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Chapter 6

General Discussion

This dissertation set out to identify ways to promote the sustainable use of effective learning strategies in university students' authentic learning settings. A large body of research has identified that learning strategies such as distributed practice, interleaving, and practice testing enhance long-term learning and are an essential part of effective self-regulated learning (SRL; Bjork & Bjork, 2011; Bjork, 1994; Bjork & Bjork, 2020; Carpenter, 2017; Dunlosky et al., 2013; García-Ros et al., 2023; Hartwig & Dunlosky, 2012; Zimmerman, 1986, 2002). While students are increasingly aware of these learning strategies, they struggle to consistently use these effective but effortful (i.e., desirably difficult) learning strategies throughout their self-study (Biwer et al., 2023; Biwer et al., 2020; Blasiman et al., 2017; Broeren et al., 2024; Rea et al., 2022). To address the gap between students' knowledge and behavior, I first aimed to understand the challenges students face when applying effective learning strategies. Second, I investigated how behavioral change approaches can support more consistent and long-term use of effective learning strategies within students' self-study. More specifically, the studies within this dissertation examined three research questions:

1. How do perceived mental effort and perceived learning relate to actual learning outcomes? (Chapter 2)
2. What are students' study habits in higher education and how do they form new and break existing habits within this context? (Chapter 3)
3. To what extent does goal-setting via implementation intentions influence students' self-regulated learning and their use of distributed practice? (Chapters 4 & 5)

In this chapter, I summarized and discussed the main findings of the studies. Additionally, I presented the strengths and limitations of the research and suggested directions for future research. Lastly, I outlined practical implications and provided a general conclusion.

Summary of Main Findings & Synthesis

Research Question 1: How do perceived mental effort and perceived learning relate to actual learning outcomes?

Prior research suggests that when learning feels effortful, learners often interpret this as a sign of low learning (Baars et al., 2020; Hui et al., 2022; Kirk-Johnson et al., 2019; Macaluso et al., 2022; Onan et al., 2022). However, without knowing how perceived mental effort and perceived learning relate to actual learning, it remains unclear whether perceived mental effort is a diagnostic cue for learning and whether regulatory decisions based on these perceptions will be accurate (De Bruin et al., 2023; De Bruin et al., 2017; Koriat, 1997).

Therefore, the first research question of this dissertation examined how perceived mental effort and perceived learning relate to actual learning outcomes in chapter 2. According to the effort-misinterpretation hypothesis (Kirk-Johnson et al., 2019), learners cannot directly access information about their own learning and therefore rely on cues such as perceived mental effort to judge how well they are learning (Kori-

at, 1997). Since higher mental effort is usually associated with lower feelings of learning (Baars et al., 2020; Hui et al., 2022; Kirk-Johnson et al., 2019; Macaluso et al., 2022; Onan et al., 2022), learners may consequently make inaccurate regulatory decisions (Baars et al., 2020; De Bruin et al., 2023; De Bruin et al., 2017). Using a meta-analytic approach (Jak & Cheung, 2020), we synthesized existing evidence on the relationships between perceived mental effort, monitoring judgments (e.g., perceived learning), and objective learning outcomes. Across studies, and in line with previous meta-analytic findings from Baars et al. (2020), perceived mental effort was negatively associated with monitoring judgments, meaning that learners who experienced learning as more effortful tended to feel that they had learned less. Monitoring judgments were positively related to actual learning outcomes, indicating that higher perceived learning corresponded to better performance. Together, these findings revealed an indirect negative relationship between perceived effort and actual learning outcomes through monitoring judgments. This indicated that when learners perceive higher mental effort, this was associated with lower feelings of learning, which aligned with actual lower learning.

In the context of the included studies, perceived mental effort acted as a diagnostic cue because learners commonly interpreted effortful experiences as signs of poor learning, and this interpretation was often accurate. These results suggest that in the included studies, learners' judgments were guided by the subjective experience of effort itself, also known as data-driven interpretation of effort (Koriat et al., 2014). Thus, perceived effort potentially signaled that a task exceeded the learner's current abilities. This interpretation would ideally prompt adaptive regulation, such as switching to an easier task or consulting worked examples to improve understanding.

However, in other contexts, this interpretation of mental effort as a sign of low learning can be problematic. Especially when engaging in desirable difficulties (Bjork & Bjork, 2011; Bjork, 1994), higher effort is not a sign of poor learning but an essential aspect that fosters retention and understanding. However, also when engaging in desirably difficult strategies such as retrieval practice or interleaving, learners often misinterpret the resulting effort as an indication of poor learning, leading them to avoid or prematurely abandon these highly effective strategies (Biwer et al., 2020; De Bruin et al., 2023; Hui et al., 2022; Kirk-Johnson et al., 2019; Onan et al., 2022). Such misinterpretations can undermine academic performance, which is positively predicted by the use of effective learning strategies (Bernardo et al., 2022; Hartwig & Dunlosky, 2012). Furthermore, the relationship between perceived mental effort, perceived learning, and actual learning outcomes may vary across time, since immediate performance can underestimate the learning that becomes evident only after a delay (Soderstrom & Bjork, 2015). This is especially crucial for desirable difficulties which sometimes show superior learning only after a delay compared to less effective strategies(Bjork & Bjork, 2011; Bjork, 1994; Bjork & Bjork, 2020; Karpicke & Roediger, 2008).

Thus, to increase students' consistent use of effective learning strategies and pre-

vent them from abandoning them prematurely due to the faulty interpretation of their perceived mental effort, the key challenge is helping learners distinguish between productive and unproductive effort during learning. Learners must learn to recognize when high mental effort reflects meaningful cognitive engagement rather than failure or inefficiency. De Bruin and colleagues (2023) propose a promising research agenda for future interventions tackling this problem. They suggest interventions that aim to help students accept, reduce, or silence effort. Accepting effort focuses on reframing effort as a natural and often beneficial part of learning. Reducing effort refers to minimizing unnecessary extraneous load, via, for example, scaffolds or worked examples, to ensure perceived mental effort reflects genuine learning rather than task overload. Similarly, supporting students in repeated engagement in desirable difficulties may also reduce perceived effort over time and additionally help learners directly experience the benefits of such strategies. Silencing effort by reducing the salience of effort cues during learning and thus preventing learners from misusing momentary effort experience as a cue for their perceived learning and subsequent regulatory decisions. Future research is needed to investigate how reframing or reducing effort perceptions influences both perceived and actual immediate and delayed learning outcomes, as well as learners' subsequent regulatory behaviors.

Overall, the findings of this dissertation suggest that one major barrier preventing university students from using effective learning strategies lies in students' perceived mental effort interpretation. By helping learners to better understand when effort signals meaningful learning, educational interventions could support sustained engagement with effective, but effortful, learning strategies.

Research Question 2: What are students' study habits in higher education and how do they form new and break existing habits within this context?

To understand how students regulate their learning toward the consistent use of effective learning strategies, we aimed to understand their study habits, as students' habitual study behavior often determines their use of effective learning strategies (Dirkx et al., 2019; Fiorella, 2020). Furthermore, habits are important predictors for behavior maintenance and thus commonly predict whether individuals can change their behavior (Rothman et al., 2009; Verplanken, 2018) and, for example, integrate new, more effortful learning strategies into their study routines. Understanding how university students form and break existing study habits to switch from ineffective to effective learning strategies is essential for understanding why effective strategies are used inconsistently. Gaining insight into these habitual processes and the barriers students encounter when trying to change them provides a necessary foundation for developing targeted support that helps students overcome these challenges and sustain the use of effective learning strategies over time.

Therefore, the second research question examined university students' study habits and how they form new or break existing habits within this context. In chapter 3, we explored the study habits of first-year university students, examining how

they form new habits and break old ones through focus group discussions. The findings revealed that while students possessed metacognitive awareness of which learning strategies are effective, they often struggled to apply them consistently. Their study behaviors were strongly shaped by assessment demands and perceived efficiency, as students tended to select learning strategies that felt most efficient for achieving short-term goals such as passing exams, even when they recognized these strategies were less beneficial for long-term learning. Behavioral change was perceived as effortful and risky and was typically undertaken only when previous strategies failed to yield satisfactory exam results. Importantly, students did not reject effective learning strategies entirely, but fluctuations in motivation further complicated their intentions to change. While many students expressed a desire to start studying earlier or adopt more effective learning strategies, especially at the beginning of the course, these intentions often weakened mid-course when competing demands or distractions arose. Toward the end of the course, often due to the pressure of the upcoming exam, students felt motivated to use effective learning strategies again. In chapter 3, we referred to these fluctuations in motivations and intention to change as the motivation roller coaster (David et al., 2024). First-year students in particular described struggling to establish consistent routines amidst broader life transitions, such as adjusting to living alone and building new social networks.

These findings of chapter 3 highlight key challenges that students face when applying effective learning strategies: high perceived effort costs, the motivation roller coaster they experience, and contextual pressures that prioritize short-term performance over long-term learning. Furthermore, these challenges also influence students' intention to use effective learning strategies. While some students had intentions to change their study behavior and incorporate more effective learning strategies, these intentions were not very concrete. According to expectancy-value cost theory (Eccles & Wigfield, 2002), such weak intentions arise when students doubt their ability to successfully use new strategies, perceive high effort costs, or undervalue the potential benefits. This is particularly relevant for desirable difficulties, which initially feel effortful and may not yield immediate results (Bjork & Bjork, 2011).

This uncertainty of immediate results also illustrates how the misinterpretation of effort observed in chapter 2 manifests in real-life learning contexts, as students often abandon effortful but effective strategies when immediate payoffs are unclear. Another central challenge that prevents students from consistently using effective learning strategies is their short-term focus on passing exams rather than building lasting understanding. Similar to prior research (Broeren et al., 2024; Rea et al., 2022), in chapter 2, many students reported seeing little need to engage in effortful learning strategies because they could pass exams without them, reflecting a performance-oriented approach that values immediate outcomes over long-term learning. Even more so, students with such a performance-oriented approach potentially experienced changing their learning strategies as risky. If the current learning strategies helped to pass exams, it could be risky to change these as this potential change might not lead to pass-

ing the exam and thus introduces a risk and uncertainty (Biwer et al., 2020). Without timely or visible feedback, students may not experience the benefits of effective strategy use, further weakening their intention to persist (De Bruin et al., 2023).

Students with more salient long-term goals, such as aspiring to become competent professionals or graduating with distinction, were better able to maintain the use of effective strategies even during periods of low motivation. In contrast, students whose goals were primarily short-term appeared more reactive to external cues like exam proximity or social distractions, which made them more vulnerable to lapses in strategy use. These patterns align with self-control and motivation research, showing that long-term goal salience enhances persistence and resistance to temptations (Duckworth et al., 2016; Fujita et al., 2006). Students with less clear long-term goals described greater difficulty prioritizing study over immediate rewards such as social activities, whereas those with salient long-term goals were willing to prioritize studying and forego social events to achieve their broader objectives. Other students described struggling to follow through with study plans when more attractive alternatives arose. This is in line with the opportunity cost model of effort (Kurzban et al., 2013), which posits that investing effort is perceived as even more costly when alternative opportunities arise. This suggests that effortful learning feels too demanding when more attractive opportunities are present and immediate success might not be salient, explaining why most students reverted to easier strategies until exams made effort investment unavoidable.

These differences in long-term versus short-term goals have important implications for promoting effective learning strategies. For students primarily focused on short-term success, it may be more persuasive to frame effective strategies in terms of efficiency rather than utility for long-term learning. Much of the existing research has emphasized their utility for long-term knowledge retention (e.g., Broeren et al., 2021), but this message may not resonate with students who do not perceive a clear need for long-term learning. For students primarily focused on short-term success, it may be more persuasive to frame effective strategies in terms of efficiency. This could be achieved by, for example, highlighting that while effective learning strategies require greater effort initially, they reduce the need for repeated study as knowledge is retained, and can save time and effort in the long run, particularly in later courses where prior knowledge is foundational for the new knowledge acquired. Instead of focusing on benefits for long-term learning, framing effective strategies in terms of efficiency could help students who focus on short-term goals to try out effective learning strategies. Once they experience positive effects, they might be more likely to incorporate them into their studying. However, more research is necessary to investigate how to frame such an efficiency argument and test whether this would be sufficient to increase students' intention to use effective learning strategies.

Furthermore, the findings from chapter 3 indicate the need to create environments where students can safely try out different learning strategies. Hereby, receiving feedback to monitor progress is essential to reduce students' perceived risk and uncer-

tainty when changing their way of studying even though they would pass exams with their previous approach. For example, Hui and colleagues (2021) found that individual performance feedback during self-testing informed students about their progress and helped them experience the effectiveness of self-testing. This experience encouraged them to use self-testing more frequently. Individual feedback may thus help students recognize when their perceived learning does not align with their actual learning, supporting more evidence-based strategy choices (Hui et al., 2022; Kirk-Johnson et al., 2019; Macaluso et al., 2022). However, future research is necessary to test whether these findings also hold for authentic learning contexts.

Alternatively, it might also help to incorporate effective learning strategies directly within the curriculum. For instance, including low-stakes assessments within courses (McDaniel et al., 2012; Trumbo et al., 2016; Wellington et al., 2015; Zarei, 2008). Next to performance improvements (for a meta-analytic overview, see (Sotola & Crede, 2021), due to the retrieval students engage in, this in-class testing could provide students with a low-threshold opportunity to practice effective strategies. This could lower the perceived risk of using self-testing as there are little consequences for it not working and thereby lowering the barrier to change. Even further, by trying these effective learning strategies out, students could actually experience their benefits firsthand, which builds confidence in their use (Carpenter, 2017; DeWinstanley & Bjork, 2004; Dobson & Linderholm, 2015; Einstein et al., 2012). These ideas align closely with developments in the assessment literature, which emphasize the formative use of multiple low-stakes assessments, also known as programmatic assessment, to guide learning and decision-making (Heeneman et al., 2021; van der Vleuten et al., 2012). Embedding frequent low-stakes assessment could promote the use of self-testing and potentially also more frequent use of other effective learning strategies, but also strengthen students' monitoring accuracy of their learning and their engagement with feedback. Importantly, though, recent research shows that the perceived stakes of programmatic assessments may vary considerably across students and contexts (Schut et al., 2018). Even when assessments are designed as low-stakes, students may still experience them as high-stakes depending on factors such as feelings of control, accessibility of results to others, and the number of assessments (Schut et al., 2018). This highlights the need to consider assessment design and students' perceptions thereof. Furthermore, future research is necessary to investigate whether effective learning strategies that are embedded within the curriculum, for example, via in-class self-testing opportunities, also translate into increased use of these learning strategies within students' self-study.

To take into consideration the fluctuations in motivation over time and the transition phases, especially first-year students experience, future research should explore how such structural supports interact with individual differences in motivation and regulation over time and identify when interventions are most effective. Personalized and well-timed interventions, particularly during transition phases such as the start of a course or pre-exam weeks, may be especially powerful, as these moments represent

windows of opportunity to influence students' learning habits and support the consistent use of effective strategies (Breitwieser et al., 2024).

Together, the findings highlight that students' ability to use effective learning strategies consistently is shaped by their goal orientations, perceived utility of strategies, and the stability of their intentions to change. Students with salient long-term goals seem more resilient to motivational dips and better able to persist using desirable difficulties, whereas those focused on short-term performance often prioritize efficiency and minimal effort. For many students, intentions to improve their study behavior remain vague, reflecting a potential cost–benefit imbalance. Students' high perceived effort and time costs involved when changing behavior, low confidence in their own abilities to change, and uncertainty about the actual benefits of effective strategies discourage sustained adoption. In environments that lack structural support or timely feedback, these tendencies reinforce reliance on old habits. Thus, promoting the consistent use of effective learning strategies requires both motivational and contextual scaffolds, such as creating opportunities to safely experiment with new strategies, reframing desirable difficulties as efficient as well as effective, and helping students formulate long-term study goals and translate these potentially abstract goals into concrete, actionable behavior.

Research Question 3: To what extent does goal-setting via implementation intentions influence students' self-regulated learning and their use of distributed practice?

Students struggle to translate their intentions to use effective learning strategies into concrete, consistent behavior. Implementation intentions (Gollwitzer, 1993, 1999) are specific "if–then" plans that link situational cues to goal-directed behaviors, and have been shown to facilitate behavior change across domains by reducing the gap between intention and action (Sheeran et al., 2025). However, their effectiveness in promoting consistent use of effective learning strategies in authentic settings remains unclear (Breitwieser et al., 2022; Endres et al., 2021; Hoch et al., 2020). Investigating whether and how implementation intentions can strengthen students' habitual use of distributed practice, therefore, provides important insights into how behavioral change principles could be leveraged to support the consistent application of desirable difficulties in students' everyday learning.

Therefore, the third research question examined to what extent goal-setting via implementation intentions can support students' self-regulated learning and promote the consistent use of distributed practice. Chapters 4 and 5 addressed this question through two experience-sampling studies conducted during four-week university courses. By monitoring students' study behavior over time after an intervention, we were able to explore behavioral change and its maintenance over time. Together, these studies demonstrated both the potential and limitations of behavioral change approaches in supporting sustained strategy use. In chapter 4, students who formulated implementation intentions did not increase their use of distributed practice com-

pared to those who merely received information about its benefits. However, students who formulated implementation intentions engaged earlier with other effective strategies, such as retrieval practice, while studying for shorter periods and reporting lower effort without compromising performance during the end-of-course exam. These findings suggest that implementation intentions may reduce the effort involved in initiating studying, thereby helping students to study more efficiently even without directly increasing distributed practice (Lally et al., 2010; Lally et al., 2011). In chapter 5, we extended this design of chapter 4 by including an additional control group and a one-week follow-up five weeks after the four-week main ESM period to examine the transfer of behavior to a new course. Consistent with chapter 4, implementation intentions did not lead to higher use of distributed practice over time or across courses. Instead, students' study behaviors followed similar temporal dynamics as in chapter 4. Namely, as exams approached, distributed practice, effort, motivation, and concentration increased across all groups, while distraction decreased. In both studies, intrinsic motivation remained stable over time. These increases in study behavior and use of effective learning strategies indicate that contextual and temporal pressures, rather than the intervention itself, were the primary drivers of study behavior. Additionally, students' use of effective learning strategies increased towards the end of the course, with more use of surface-level strategies such as summarizing and rereading at the beginning of the course, and more retrieval-based methods and distributed practice toward the end of the course. This shift could indicate that students do not fully understand the benefits of effective learning strategies, for instance, they may view testing merely as a way to monitor understanding and identify knowledge gaps shortly before an exam, rather than as a strategy that also enhances long-term retention itself. This aligns with prior research suggesting that when using self-testing, students commonly do so to monitor their knowledge at the end of learning instead of using it as a tool for learning (Geller et al., 2018; Hartwig & Dunlosky, 2012; Kornell & Bjork, 2007). Furthermore, the interpretation that students do not fully understand the purpose of effective learning strategies is supported by findings from Abel et al. (2024), who showed that when students were aware of the underlying goal of a learning task (e.g., differentiating between categories), they were more likely to engage in the effortful yet effective learning strategy. On the other hand, the increase in effective strategy use before exams may suggest that students find it difficult to engage in effortful learning when stakes are low, which is in line with our findings from chapter 3. During periods of lower motivation or urgency, such as mid-semester, students often reverted to low-effort, habitual behaviors. This pattern aligns with dual-process models of habit formation (Wood & Rünger, 2016), which propose that when motivation or self-regulatory resources are limited, automatic, context-triggered behaviors tend to dominate over deliberate, goal-directed actions. This interpretation that students struggle to engage in effortful learning when stakes are low, also nuances the earlier argument regarding frequent low-stakes assessments, such as in-class testing opportunities. While embedding these within the curriculum may low-

er the barrier to adopt effective learning strategies, such approaches might be insufficient if students lack the motivation to engage with them when perceived stakes are low. As Schut et al. (2018) found, learners' perceptions of assessment stakes can differ from the intentions of educators, suggesting that further research is necessary to investigate how to best address motivational and contextual fluctuations so that low-stakes practice opportunities are effectively supporting self-regulated use of effective learning strategies.

Notably, in chapter 5, students who initially intended to use distributed practice were more likely to do so regardless of group, suggesting that intention strength instead of goal-setting via implementation intentions, predicted use of distributed practice. Only in chapter 5, we explored transfer changes to a new course. There were no group differences in study behavior during the follow-up period, highlighting that without reinforcement or environmental scaffolding, behavioral change remains transient. Instead, students' mean weekly use of distributed practice during the main period positively predicted students' engagement in distributed practice during the follow-up week, indicating that when students had a stronger habit of using distributed practice during the main ESM period, they were also more likely to engage in distributed practice during the follow-up period. When relating this finding to chapter 3, it could further strengthen the interpretation that students with long-term goals are able to better integrate effective learning strategies consistently within their learning. It also further illustrates the central role habits seem to play in consistent use of effective learning strategies.

The findings of both chapters provide insight into why implementation intentions may not have produced sustained effects. Incorporating effective learning strategies such as distributed practice is a complex behavior involving multiple steps such as scheduling review times, preparing materials, and evaluating performance. This multiple step procedure could make it more difficult to routinize through a single cue–response association (Phillips & Mullan, 2023). This aligns with research distinguishing between instigation habits (automatic initiation of a behavior in response to a cue) and execution habits (automatic performance of the behavior itself; Phillips & Gardner, 2016; Phillips & Mullan, 2023). Following behavioral change literature in the health domain, forming instigation habits to initiate studying, such as opening a flashcard app after lectures or walking to the library, may be easier to automate compared to the entire behavioral sequence of distributed practice or other effective learning strategies. This also aligns with findings from health psychology showing that combining habitual instigation with variable execution might be optimal to sustain complex behaviors over time while maintaining motivation and reward (Mennella et al., 2008; Mullan & Novoradovskaya, 2018; Sylvester et al., 2016). Applied to the current findings, this suggests that implementation intentions may best support the initiation of consistent study behavior. Once this routine is established, it might be easier to incorporate the use of effective learning strategies within this pre-established routine. The cue-context response underlying implementation intentions might be espe-

cially effective when focusing on automating initiation of studying rather than entire study routines that include effective learning strategies.

However, future research is necessary to better understand habit formation for complex behavior, and, in particular, whether distinguishing between instigation habits (initiating a study session) and execution habits (carrying out the strategy) is effective to promote the use of effective learning strategies and whether the formation of such micro-habits as opening the flashcard software can increase the use of effective learning strategies.

Furthermore, embedding support within curricula such as ready-made question banks, automated flashcard tools, or low-stakes assessments could further reduce initiation costs for students. By reducing the steps necessary for students to take to incorporate effective learning strategies, teachers and institutions can help students form small, repeatable study routines that fit and facilitate the use of effective learning strategies within their daily lives. Evidence from self-regulation research in other fields, such as health psychology, shows that sustainable behavior change is best achieved through small, repeatable actions that lower effort barriers and fit naturally into existing routines (Lally & Gardner, 2013; Verplanken et al., 2018; Wood & Neal, 2016). Teachers and institutions can play an important role by providing low-effort starting opportunities (e.g., ready-made practice materials), emphasizing the short-term benefits of effective strategies, and designing assessments that reward continuous engagement and long-term understanding rather than last-minute studying. More research is necessary to understand whether and how such embedded support increases students' use of effective learning strategies.

Overall, the findings of chapters 4 and 5 demonstrate that while goal-setting via implementation intentions alone was insufficient to increase students' consistent use of distributed practice, behavioral interventions remain a promising avenue for supporting effective strategy use. Students' intentions to use effective learning strategies emerged as a predictor of actual engagement, highlighting that fostering specific intentions to use effective learning strategies may be critical. The limited effect of implementation intentions likely reflects the complexity of the target behavior as using distributed practice requires multiple coordinated steps, making it difficult to routinize through a single cue–response link. Future work should therefore explore how micro-habits that automate the initiation of studying can serve as accessible starting points for complex, effortful strategies. Embedding support within the learning environment, for instance, through ready-made question banks, automated retrieval tools, and low-stakes assessments, could reduce initiation costs and help students sustain effective strategies even when motivation fluctuates.

Moreover, both chapters also highlight the relevance of using ESM for SRL research. Even further, the regular prompting of ESM itself may have prompted students to reflect on their own learning behaviors more systematically, thereby enhancing metacognitive awareness and potentially influencing behavior. Future research is necessary to investigate the influence of prompting students to monitor regular study

behavior on increasing the use of effective learning strategies.

Strengths, Limitations, and Future Research Directions

A key strength of this dissertation lies in its longitudinal and dynamic perspective on learning strategy use. By employing methodologies such as experience sampling and focus group discussions, the studies captured week-to-week fluctuations in students' strategy use, motivation, and effort, providing richer insights than traditional pre-post designs or one-time questionnaire administration to capture learning strategy use. This approach closed an important methodological gap by examining the use of learning strategies over time, which enabled a more authentic understanding of how self-regulated learning unfolds in real academic contexts. Another strength is the methodological diversity and complementarity of the studies. By combining a meta-analysis, focus group discussions, and longitudinal experience-sampling designs, the research examined both broad trends and nuanced individual experiences. Finally, this dissertation adopted a student-centered perspective, giving voice to learners' experiences and challenges and thereby shifting the focus from what students should do to understanding why they behave as they do.

Despite these strengths, several limitations must be acknowledged, which also point toward future research directions. First, although the studies captured temporal fluctuations in SRL, most analyses were conducted at the group level, leaving intra-individual dynamics less visible. This was a deliberate methodological choice to ensure sufficient statistical power and interpretability across time. Future research should build on this by adopting a dynamic, intra-individual perspective, combining longitudinal experience-sampling with qualitative interviews in which data is fedback to students to trace how and why individual students regulate learning across time and contexts. Such designs would provide a more fine-grained understanding of intra-individual dynamics.

Second, the dissertation relied primarily on self-report measures, which may not always correspond to actual behavior or performance. Self-report measures are common in SRL research and allow for practical and frequent data collection within students' authentic learning contexts. Through the repeated measurement of ESM, self-report in the ESM studies typically has higher validity than one-time questionnaires (Csikszentmihalyi et al., 1977). Nevertheless, to further strengthen validity, future studies could integrate trace data (e.g., learning management system logs) or observational measures to triangulate students' self-reported experiences with more objective behavioral evidence.

Third, the student samples in chapters 3-5 were drawn from a specific educational context, which were students at the Faculty of Health, Life Sciences and Medicine at Maastricht University. These students had prior exposure to study skills training, such as the Study Smart Training (Biwer et al., 2020) and studied within a problem-based learning (PBL) curriculum (Dolmans et al., 2005; Moust et al., 2005). While this may limit generalizability, it also highlights the persistence of strategy-use

challenges even when students have knowledge about effective learning strategies and study within a supportive environment that promotes active learning. Future work should examine whether similar barriers and dynamics emerge in more traditional, lecture-based programs or in disciplines with different pedagogical approaches.

Fourth, across most studies in this dissertation, the primary focus was on students' use of effective learning strategies rather than on direct measures of learning. While chapters 4 and 5 examined how formulation of implementation intentions influenced strategy use, they also explored whether these changes were associated with increased end-of-course performance. Similarly, chapter 2 included immediate performance on a learning task as an outcome variable. These performance indicators represent proximal learning outcomes and do not necessarily reflect long-term retention, understanding, or transfer of knowledge (Soderstrom & Bjork, 2015). Thus, while some learning outcomes were assessed, the dissertation contains few measures that allow strong conclusions about long-term learning. Even though long-term learning was not the primary focus of the current dissertation, future research should examine how the consistent use of effective learning strategies shapes students' long-term learning. Conducting such research in authentic educational settings requires careful consideration, as students' long-term learning trajectories are shaped by many interacting factors, such as changes in their study behavior, differences in instructional contexts, and shifts in motivation. These changes make isolating the long-term effects of specific learning strategies complex. Practical aspects such as sustained participation, repeated testing, and stable learning conditions also play an important role in designing such longitudinal research. Acknowledging these considerations is essential for advancing future work that aims to understand how durable effective strategy use contributes to long-term learning rather than immediate performance alone.

Beyond addressing these methodological considerations, several additional lines of future research emerge from the findings. The rationale for each of these research avenues has been discussed in more depth in the sections above and is reiterated briefly here. Future work should clarify when effort signals productive versus unproductive struggle and test how reframing interventions (e.g., S2D2; De Bruin et al., 2023) influence students' interpretations of effort and its perceived utility. Moreover, further research is needed on habit formation in complex self-regulated behaviors. Distinguishing between instigation habits (initiating study sessions) and execution habits (carrying out strategies; Phillips & Mullan, 2023) could clarify how multi-step learning behaviors, such as retrieval or distributed practice, become routinized. Testing whether micro-habits with low initiation costs, such as opening a study app, walking to a study space, or blocking distractions, support consistency represents a particularly promising avenue.

In addition, future studies should investigate personalized and well-timed interventions (Breitwieser et al., 2024). Because self-regulated learning challenges vary over time and between students, interventions should be tailored to individual bottlenecks and introduced at key transition phases (e.g., entering university, beginning

a new course, or preparing for exams), which may serve as windows of opportunity for change. Finally, research should examine how individual and structural support can be integrated to sustain behavioral change over time. Adaptive interventions that combine goal-setting, cue formation, and contextual scaffolds (such as embedded retrieval practice or automated feedback) could enhance both the immediate and long-term effectiveness of behavioral change strategies.

Taken together, these directions emphasize that understanding and supporting the use of effective learning strategies requires investigating learning dynamically within authentic academic contexts. Future research can advance both theory and practice by identifying how students transform effortful learning into sustainable habits that persist beyond temporary motivation or contextual pressures.

Practical Implications

The findings of this dissertation highlight several practical implications for supporting students in adopting and sustaining effective learning strategies. These implications center on reducing unnecessary effort costs, reframing effort and utility beliefs, strengthening habit formation, and aligning educational environments with long-term learning goals, and creating structural opportunities to use effective learning strategies. The implications are introduced per target group.

For students, one of the clearest barriers to sustained use of effective learning strategies is the effort they demand. Because students often avoid strategies that feel costly in the moment, especially when motivation is low, supporting small, repeatable actions that make studying easier to start is essential (Wood & Neal, 2016). Forming micro-habits and initiation cues (e.g., opening a flashcard app at the start of a study session, walking to the library after lectures) can lower initiation barriers and free up cognitive resources for learning itself. Forming implementation intentions could potentially help to reduce friction to start using effective learning strategies such as incorporating practice testing, though they likely require reinforcement over time to prevent relapse into old habits (Breitwieser et al., 2022). Goal-setting should be specific and actionable and realistic rather than abstract. Forming and relying on consistent behavior could help to accept or silence the effort required when using effective learning strategies (De Bruin et al., 2023).

Teachers play an important role in shifting the perception of effective learning strategies from something that merely makes learning more effective to something that can also make learning more efficient. Emphasizing that effortful strategies can reduce overall study time, lower exam stress, and improve retention across courses may be especially persuasive for students who are primarily focused on short-term performance. Teachers can support this shift by helping students interpret their experience of effort, reducing the perceived costs of strategy use, and making the immediate benefits of effective strategies more visible (De Bruin et al., 2023). This can be done, for example, by providing continuous feedback or by offering ready-to-use materials such as question banks, online practice platforms, or collaborative flashcard

tools, which lower the preparatory effort required to use effective learning strategies and increase the likelihood that students will engage with them. Furthermore, embedding strategies, such as retrieval practice or distributed review, directly into courses could help students experience their benefits firsthand, especially when paired with formative feedback (Hui et al., 2021).

For institutions, aligning learning objectives, teaching activities, and assessments that focus on understanding and transfer of knowledge rather than short-term performance could help normalize continuous learning (Biggs, 1996). Frequent low-stakes assessments, progress-based grading (Van der Vleuten et al., 2010), and peer-support opportunities (e.g., study groups, co-created practice materials) could encourage consistent studying instead of last-minute cramming. Creating environments that value effortful learning, reduce unnecessary effort, and leverage co-regulation opportunities so students can share experiences with using effective learning strategies or creating opportunities to engage in desirable difficulties without risking failing high-stakes exams could further facilitate the maintenance of effective learning strategy use.

Conclusion

This dissertation examined the challenges university students face when applying effective learning strategies and how behavioral change approaches can support their consistent use of these strategies. The findings revealed that students' use of effective learning strategies changes over time, influenced by their motivation, perceived mental effort, and environmental demands. Commonly, students have a persistent knowledge-behavior gap. Although they often know which strategies are effective, they struggle to apply them consistently because effort feels costly, utility is framed in long-term rather than immediate terms, and academic demands can be met even when focusing on short-term performance. Students tended to view effort as a signal of poor learning, which can be detrimental in the context of effective learning strategies where effort does not signal low learning. Forming habits around effective strategies also proved challenging, reflecting the complexity of behaviors such as distributed practice that require multiple steps and thus might be more difficult to automate than simpler behaviors. Furthermore, while habits seem to be crucial in students' consistent use of effective learning strategies, more research is necessary on how to support students in forming these habits. Together, these findings highlight that sustainable use of effective learning strategies requires more than metacognitive awareness. It depends on concrete intentions, supportive contexts, and scaffolds that lower initiation costs and make productive effort both visible and worthwhile. Promoting durable use of effective learning strategies, therefore, likely requires more structural support and environments that value and normalize effortful learning, provide timely feedback, and align structural incentives with long-term learning rather than short-term performance to incentivize students to form habits that incorporate effective learning strategies.

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Impact

Using effective learning strategies is essential for long-term learning and academic success. Yet, in practice, many students rely on familiar but ineffective strategies such as rereading or last-minute cramming. These strategies often feel easier and more comfortable, but they rarely lead to lasting learning or understanding. Many students struggle with this, and over time, this ineffective studying can make it harder to keep up with coursework, perform well on exams, or stay motivated. Therefore, the objective of this dissertation was to better understand why students struggle to use effective learning strategies sustainably and to explore support approaches that may help them do so within their authentic learning contexts. I approached these questions from several angles across four research studies, including a meta-analysis, focus groups, and two experience-sampling studies. The individual chapters and the summary of this dissertation describe these studies in more detail. Overall, the results of this dissertation indicate that the reasons why students struggle to use effective learning strategies sustainably are multifaceted. They highlight how students interpret their mental effort during learning, how existing study habits guide their behavior, how difficult it is to translate intentions into action and change study habits, and how strongly students' environment shapes their study behavior. While more research is necessary, these insights also point toward several promising approaches for helping students build more sustainable study habits.

In this impact chapter, I draw on the broader relevance of self-regulated learning and the findings of my dissertation to address three assumptions I frequently encountered in my own teaching and in conversations with peers. I use these assumptions as a lens to reflect on the challenges students face and on possible ways to support more effective learning. These assumptions often shape how students and teachers make sense of learning and why certain strategies are adopted or avoided. By revisiting them through the perspective of my research, I aim to offer a clearer understanding of these challenges and outline initial ideas for how students, teachers, and institutions can support more sustainable study behaviors. These ideas are not final answers, but they represent potential first steps informed by my findings.

"Learning happens primarily in the classroom."

A belief I frequently encounter in conversations with both university students and teachers is that learning primarily occurs during lectures, tutorials, or practicals. What students do at home, how they study, which strategies they choose, and thus how they regulate their learning, is often seen as separate from, or even outside the scope of, formal teaching. From this perspective, self-regulated learning becomes a private responsibility or even a blind spot rather than an educational priority. Yet the reality is that, especially at university, a large part of students' learning takes place outside the classroom. Students' ability to effectively self-regulate their learning during their self-study strongly influences their understanding, academic performance, and well-being. When students rely on ineffective learning strategies, they may work hard without learning, which can cause stress, discouraging results, and, in some cas-

es, even dropout.

Understanding and supporting students' self-regulated learning is therefore not only academically important but also socially relevant. Students arrive at university with diverse educational backgrounds, meaning they differ in their familiarity with effective learning strategies and their experience using them. If higher education relies predominantly on what happens in the classroom, these differences can widen rather than narrow. Strengthening self-regulated learning skills can enhance students' performance, long-term learning, and reduce stress, contributing to more equitable and inclusive educational environments.

This dissertation addresses an often-overlooked part of learning by examining how students actually study in their authentic setting, why effective strategies are difficult to sustain, and what support may help. The findings of my studies underline that many challenges in students' learning arise outside the classroom, during students' self-study. For example, the focus groups (Chapter 3) show that students struggle to use effective strategies consistently because established habits with less effective strategies feel familiar and have enabled them to pass exams. The experience-sampling studies (Chapter 4 & 5) further demonstrate that students' study behavior and strategy use fluctuate with environmental cues such as exam proximity, highlighting that context strongly shapes what students do outside the classroom. By making these dynamics visible, this dissertation provides concrete evidence that improving learning requires supporting what happens outside the classroom. Helping students overcome the challenges they experience during self-regulated learning is essential for fostering effective and sustainable learning in higher education.

"If learning feels hard, something must be wrong."

Another assumption I was frequently confronted with is that learning should feel smooth and that difficulty is a sign of something going wrong. The findings of this dissertation show that this belief is partly grounded in students' experiences. Across the studies included in the meta-analysis (Chapter 2), higher mental effort was often linked to lower perceived learning, which in turn was related to lower actual learning. In other words, when a task feels harder, students tend to believe they are learning less, and they are indeed performing worse. However, this relationship is more complex than it first appears. Mental effort, perceived learning, and actual learning do not always move in the same direction. Students' interpretation "if it feels hard, I'm learning less" is accurate for some types of tasks but misleading for others. For example, when using effective learning strategies such as retrieval practice or spacing, students typically experience more mental effort than when using less effective ones. Yet, this additional effort is exactly what makes these strategies more effective, as it reflects cognitive engagement that supports lasting learning. Here, the assumption that "feeling more effort means less learning" becomes counterproductive, because students may abandon effective strategies even though they work. At the same time, effort is not always a positive signal. Excessive effort due to, for example, poor task design or distrac-

tions may indicate cognitive overload, and in those situations, reducing effort is appropriate. The challenge, therefore, is not to teach students to ignore effort altogether but to help them understand what their effort experience is telling them.

Students need support in developing this nuanced interpretation of their effort experience during learning. While research on how to do this optimally is still developing, several approaches appear promising. First, raising awareness about the complex relationship between effort, perceived learning, and actual learning may help students make sense of their discomfort during learning. Understanding that productive learning often involves effort may help students stick to effective strategies rather than abandoning them. Teachers could actively support students in this by explaining why effort arises during effective learning to help normalize the experience. Furthermore, teachers could also offer low-stakes practice engagement in effective learning strategies. Offering opportunities to experience effortful strategies without grade pressure may help students experience that effortful learning leads to long-term benefits. The focus group findings suggest that students are more willing to use effective learning strategies when the necessary materials are readily available, as students with access to past exam questions used them frequently, whereas those without such resources found generating practice questions too effortful and were less likely to engage in retrieval practice. Thus, supplying practice materials or offering support in creating them can reduce initiation costs and make it easier for students to adopt and maintain effective learning strategies.

"Once students know about effective strategies, they will use them."

Another assumption I often encountered is that once students are taught which learning strategies are effective, they will naturally use them during their self-study. While knowing about effective strategies is an important first step, the findings of this dissertation suggest that knowledge alone does not necessarily lead to behavior change. The focus group discussions indicated that many students continue to rely on familiar habits such as rereading, highlighting, or summarizing, which feel comfortable, efficient, and safe, especially under pressure. Because these habits have helped students pass exams in the past, switching to more effortful but more effective strategies can feel risky or unnecessary. In our focus groups, several students noted that they could pass their university exams using their existing approaches, reinforcing their sense that change is not worth the effort. Furthermore, the experience-sampling studies suggest that even when students make concrete plans on how to incorporate effective learning strategies, following through proves difficult. Here, implementation intentions, the "if–then" plans often expected to support behavior change, did not help students distribute their learning more consistently. Students' actual study behavior fluctuated far more with environmental cues such as exam proximity. This finding suggests that planning when and how to use effective learning strategies is not enough, potentially due to the multiple steps required in the complex, sequential strategies like spacing, which require repeated initiation over time.

For complex behaviors, habit research distinguishes between initiating a behavior (instigation) and completing the steps that follow (execution), and although this line of research is still emerging, treating these processes separately may be a promising way to help students build sustainable study habits.

Taken together, this dissertation's findings show that supporting students in using effective learning strategies requires more than providing knowledge, being motivated, or formulating concrete plans. Students' study behavior is strongly shaped by the demands and opportunities of their learning environment. Thus, when the environment does not facilitate and incentivize the use of effective learning strategies, students likely rely on familiar habits, regardless of their intentions and knowledge. Therefore, meaningful support should involve creating a) incentives for change that help students see the value of adopting effective learning strategies, and b) structured opportunities that make effective strategies easier to initiate and maintain. Approaches that lower the effort required to get started, allow students to experience the benefits of effective strategies, or that embed effective strategies directly into the environment may offer promising pathways for helping students develop more sustainable study routines. Such support could include regularly scheduled low-stakes retrieval activities, ready-made practice materials that reduce students' preparatory effort, or a course structure that naturally encourages effective learning strategies.

Concluding Reflections: Scientific Impact, Dissemination & Future Steps

Beyond these practical implications, this dissertation also contributes to the scientific understanding of how students study and why effective strategies are so difficult to use sustainably. It advances existing theories of self-regulated learning by underlining that students' perceived mental effort during learning is not a straightforward indicator of learning. By approaching the use of effective learning strategies from a behavioral change perspective, this work adds a new conceptual frame for understanding the persistence of ineffective study habits and the challenges of initiating effective ones. Methodologically, the combination of qualitative and quantitative methods, and the use of experience-sampling, offers a more nuanced view of students' daily studying compared to retrospective surveys or controlled laboratory tasks.

To ensure impact, I have shared these insights with the scientific community through open-access publications and presentations at conferences such as the annual meeting of the Junior Researchers of European Association of Research on Learning and Instruction (EARLI; JURE) 2022, EARLI's Special Interest Group (SIG) "Metacognition and Self-Regulated Learning" 2022 & 2024, EARLI's SIG "Instructional Design & Technology Enhanced Learning" 2022 & 2024, Psychonomics 2022 & 2024, Onderwijsresearchdagen (ORD) 2023, and EARLI 2023 & 2025. Elements of this work have also been disseminated through expert network meetings such as the EARLI Emerging Field Group "Effort Regulation & Monitoring" 2022, the

Self-Regulated Learning in Digitized Schools (SeReLiDis) network meetings in 2023 & 2025, and the Self-Regulating Network (SeReNe) in 2025 to add to ongoing discussions in educational psychology research. I have also engaged in practice-oriented dissemination through my work as a trainer and consultant for the "Study Smart" learning strategy program. I contributed to updating and expanding the training materials, supported programs in embedding the training within their specific context, and provided teacher trainings at Maastricht University, Leiden University, and the University of Applied Sciences Utrecht. The insights gained during my research have shaped how I approach these trainings and my perspective on how to encourage students to use effective learning strategies.

Together, these dissemination efforts reflect the broader aim of this work, which is to help students, teachers, and institutions better understand learning and to support more sustainable study behaviors in students' authentic learning context.

Summaries

English Summary

Especially in higher education, learners need to plan, monitor, and execute (i.e., self-regulate) most of their learning autonomously. Doing so effectively, for instance, by using effective learning strategies, is essential for academic success. Although students are becoming increasingly aware of the importance of using effective learning strategies, many continue to struggle to apply them and instead rely on less effective ones. This discrepancy between what is known to be effective and what students actually do represents a persistent challenge in promoting the use of effective learning strategies. Research has identified several potential barriers that may explain why students struggle to use effective learning strategies regularly. However, little is known about how these barriers interact in authentic learning contexts or how students can be supported to overcome them to incorporate effective learning strategies more sustainably. The present dissertation addresses this gap by investigating why students fail to use effective learning strategies sustainably and exploring the promotion of sustainable strategy use through behavioral change approaches.

To address the research aims, I conducted four studies. In chapter 2, I investigated how learners' perceived mental effort and perceived learning relate to actual learning. In chapter 3, I explored university students' study habits and how they form new and break existing habits within this context. In chapters 4 and 5, I investigate to what extent goal-setting via implementation intentions influences university students' self-regulated learning and their use of distributed practice.

According to the cue-utilization theory (Koriat, 1997), learners are unable to directly access information about their own learning, and thus often use cues such as perceived mental effort to judge their learning. Past research indicates that learners often interpret their mental effort experience as a sign of low learning. However, so far, it is unclear how this commonly relates to actual learning outcomes. Using a meta-analytic structural equation model, I synthesized evidence on the relationships between perceived mental effort, monitoring judgments, and actual learning outcomes. I extracted data from 35 manuscripts with 83 independent samples, 236 effect sizes, and a total sample size of N = 3973. Across studies, perceived mental effort was negatively associated with monitoring judgments ($\beta = -.19$), meaning that higher perceived mental effort was linked to lower feelings of learning or understanding. Monitoring judgments were positively associated with actual learning ($\beta = .29$), meaning that higher feelings of learning or understanding, related to actual higher learning. Together, these effects produced an indirect negative relationship between perceived mental effort and actual learning outcomes via monitoring judgments ($\beta = -.05$). This pattern suggests that learners often interpret effortful learning experiences as signs of poor learning, which aligned with actual lower performance. In the contexts captured by the included studies, this interpretation was consistent with the cue-utilization theory. The latter suggests that perceived mental effort is a diagnostic cue used during monitoring of learning as it correlates with lower perceived learning and lower actual learning. The findings of the study highlight the need to support learners in interpret-

ing their perceived effort during learning. While in the contexts of the included studies, higher perceived mental effort was a diagnostic cue correlating with actual lower learning, this might not always be the case. For example, in the context of desirable difficulties, interpreting perceived mental effort as a sign of poor learning might mistakenly cause students to disengage prematurely, since effort is an essential aspect of the effectiveness of desirable difficulties.

To gain insight into how students sustain the use of effective learning strategies, in chapter 3, I explored university students' study habits and their experiences forming new and breaking old habits as habitual behavior is commonly a predictor of behavior. Using a qualitative approach, I invited 29 first-year students to six focus group discussions to gain richer understanding of their habitual study behaviors and challenges associated with incorporating effective learning strategies. Thematic analysis revealed that students' learning strategy choices were often shaped by the type of assessment and the perceived efficiency of reaching short-term goals. While students demonstrated some metacognitive knowledge, behavioral change was described as effortful and undertaken only when deemed necessary, for example, if previous learning strategies did not help to pass an exam. Other students mentioned that they had intentions to change their study behavior, but were not sure how. Motivation fluctuated throughout the semester, influencing whether students acted upon their intentions to change. Furthermore, navigating life challenges such as the transition from high school to university affected students' study behavior. The findings provided insights into the factors that shape students' intentions to change their learning behaviors and highlight the need to align assessment methods with lifelong learning objectives. Moreover, supporting students in setting long-term academic goals that encourage the development of study habits could foster durable learning and consistent use of effective learning strategies to reach these long-term goals.

As goal-setting has been shown to be effective to initiate behavioral change in other domains, in chapter 4, I investigated whether goal-setting via implementation intentions could increase university students' use of distributed practice. Additionally, I explored students' SRL throughout a four-week university course. Using the experience sampling method (ESM), I monitored students' (N = 85) daily use of distributed practice and other study behavior such as their study motivation, study effort and study satisfaction and compared how this differed between students who set specific implementation intentions to incorporate distributed practice and obstacle plans that could hinder them from achieving their goal (n = 35) compared to students who were merely informed about the benefits of distributed practice and goal-setting at the beginning of the study (n = 50). Although implementation intentions did not increase the use of distributed practice, students in this group adopted more effective strategies, such as practice testing early in the course, studying for shorter durations, reported lower study effort, and showed increased concentration toward the end of the course while performing similarly to the control group at the end-of-course exam. Across both groups, study behaviors shifted over time, with study duration, use of

effective learning strategies, motivation, effort, and study satisfaction increasing near exams. Qualitative analysis of the implementation intentions suggests that students were generally able to formulate goals on how to regularly review previously learned content, yet these goals often lacked specificity and concreteness. Overall, the findings indicate that while implementation intentions did not directly increase the use of distributed practice, they may support more efficient study behavior, such as the earlier adoption of retrieval-based strategies. Furthermore, the results show that students' learning behaviors change, with exam proximity strongly shaped how students allocate effort and motivation. These patterns underscored the importance of designing assessment methods that encourage consistent learning for long-term retention rather than short-term performance. Moreover, the study illustrates the value of examining self-regulated learning processes over extended periods using ESM to capture how students dynamically adjust their study behaviors in response to changing academic demands.

In chapter 5, I used a similar design as in chapter 4, and extended it by including three groups and adding a one-week follow-up ESM period five weeks later to investigate potential transfer effects. In the implementation intention group (N = 29), students formed implementation intentions, in the information-only group (N = 36), students received only information about distributed practice and its benefits, and the control group (N = 35) received no additional input. Over a four-week course, I used ESM (k = 1998) to capture daily study behavior such as learning strategy use, study duration, motivation, and effort. Five weeks later, we had a one-week follow-up ESM period (k = 343) to assess potential transfer of study behavior and goal achievement to a new course. Similar to chapter 4, results suggest that formulating implementation intentions did not significantly increase students' use of distributed practice compared to control conditions. Instead, students' individual intentions to use distributed practice predicted their actual engagement in distributed practice. Changes in study behaviors over time were primarily influenced by contextual factors, particularly exam proximity. Across groups, as exams approached, students reported greater effort, study time, concentration, extrinsic motivation, and satisfaction, along with reduced distraction. Independent of group, use of distributed practice in the next course was predicted by use of distributed practice during the main ESM period. These results suggest that shifts in students' learning behaviors are driven more by exam proximity than by goal-setting and underscore the difficulty of translating intentions into consistent behavioral change. Especially for complex strategies like distributed practice that require sustained effort over time, educational interventions may be more effective when they help students establish an instigation habit that fosters initiation of regular studying. Moreover, assessment practices that reward long-term learning rather than short-term performance could better support students in developing durable self-regulated learning habits.

In chapter 6, I synthesized and discussed the results and implications of the studies in relation to the research questions of this dissertation and related scientific liter-

ature. The findings of this dissertation indicated that students' engagement with effective strategies fluctuated over time, shaped by motivation, interpretation of mental effort during learning, and contextual pressures. Despite understanding which strategies are effective, many students failed to use them consistently as effort felt costly, benefits of using effective learning strategies were not salient to all students, and short-term performance could be achieved when using less effortful strategies. Effort was frequently misinterpreted as a sign of poor learning, creating a barrier to adopting desirable difficulties that require effort. The development of habits around effective study behaviors proved complex, potentially because learning strategies such as distributed practice involved multiple steps that were difficult to automatize. Sustained strategy use, therefore, likely depends not only on metacognitive knowledge but also on specific intentions to use them and environmental scaffolds and support that, for example, help interpret effort during learning, reduce effort required to engage in effective learning strategies, and align the utility of effective strategies with students' goals. Ultimately, fostering consistent use of effective learning strategies likely requires educational environments that normalize effortful learning, provide support, and align incentives with long-term understanding rather than short-term performance.

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Nederlandse Samenvatting

Met name in het hoger onderwijs moeten studenten het merendeel van hun leren zelfstandig plannen, monitoren en uitvoeren, oftewel zelfreguleren. Om academisch succes te behalen is het essentieel dat ze deze zelfregulatie op een effectieve manier doen, bijvoorbeeld door effectieve leerstrategieën te gebruiken. Hoewel studenten zich steeds meer bewust worden van het belang van effectieve leerstrategieën, hebben velen moeite om deze toe te passen en gebruiken ze in plaats daarvan minder effectieve strategieën. Deze discrepantie tussen wat bekend staat als effectief en wat studenten daadwerkelijk doen, vormt een voortdurende uitdaging bij het stimuleren van het gebruik van effectieve leerstrategieën. Onderzoek heeft verschillende mogelijke barrières aan het licht gebracht die mogelijk verklaren waarom studenten moeite hebben om regelmatig effectieve leerstrategieën toe te passen. Er is echter weinig bekend over hoe deze barrières interageren in authentieke leeromgevingen en hoe studenten ondersteund kunnen worden om deze barrières te overwinnen en zo effectieve leerstrategieën te integreren. Dit proefschrift speelt hierop in door te onderzoeken waarom studenten effectieve leerstrategieën niet consequent toe passen en hoe gedragsveranderingsbenaderingen het consequente gebruik van effectieve leerstrategieën kunnen bevorderen.

Om de onderzoeksdoelstellingen te bereiken, heb ik vier studies uitgevoerd. In hoofdstuk 2 onderzocht ik bij studenten hoe de ervaren mentale inspanning en het ervaren leren verband houden met het daadwerkelijke leren. In hoofdstuk 3 bestudeerde ik de studiegewoonten van universiteitsstudenten en hoe zij nieuwe gewoonten aanleren en bestaande gewoonten afleren in deze context. In hoofdstukken 4 en 5 heb ik onderzocht in welke mate doelen stellen via implementatie-intenties het zelfregulerend leren van universiteitsstudenten en hun gebruik van gespreid leren beïnvloedt.

Volgens de cue-utilization-theory (Koriat, 1997) verkrijgen lerenden geen directe informatie over hun eigen leerproces en gebruiken ze daarom vaak cues zoals hun ervaren mentale inspanning om hun leerproces zelf te beoordelen. Uit eerder onderzoek blijkt dat lerenden hun ervaren mentale inspanning vaak interpreteren als een teken van slecht leren. Tot nu toe is echter onduidelijk hoe dit zich doorgaans verhoudt tot daadwerkelijk leren. Aan de hand van een meta-analytisch structuurvergelijkingsmodel vatte ik bewijs over de relaties tussen ervaren mentale inspanning, zelfbeoordelingen en daadwerkelijke leerresultaten samen. Ik extraheerde gegevens uit 35 manuscripten met daarin 83 onafhankelijke steekproeven, 236 effectgroottes en een totale steekproefomvang van N = 3973. Ervaren mentale inspanning was negatief gecorreleerd met zelfbeoordelingen (β = -.19), wat betekent dat een hogere ervaren mentale inspanning gelinkt was aan een lager gevoel van leren of begrip. Zelfbeoordelingen waren positief gecorreleerd met daadwerkelijk leren (β = .29), wat betekent dat een sterker gevoel van leren verband hield met meer daadwerkelijk leren. Samen zorgden deze effecten voor een indirect negatief verband tussen ervaren mentale inspanning en daadwerkelijk leren via zelfbeoordelingen (β = -.05). Dit patroon sug-

gereert dat lerenden inspannende leerervaringen vaak interpreteren als een teken van slecht leren, wat overeenkomt met daadwerkelijk lagere prestaties. In de contexten van de geïncludeerde studies kwam deze interpretatie overeen met de cue-utilization-theory. Deze theorie suggereert dat ervaren mentale inspanning wordt gebruikt als een diagnostische cue tijdens leerbeoordeling, aangezien deze correleert met een lager gevoel van leren en een lagere daadwerkelijke leerprestatie. De bevindingen van het onderzoek benadrukken de noodzaak om lerenden te ondersteunen bij het interpreteren van hun ervaren inspanning tijdens het leren. Hoewel in de context van de opgenomen studies een hogere ervaren mentale inspanning een diagnostische cue was die correleerde met daadwerkelijk slechter leren, is dit misschien niet altijd het geval. Zo kan het interpreteren van ervaren mentale inspanning als een teken van slecht leren in de context van wenselijke moeilijkheden er ten onrechte toe leiden dat studenten voortijdig afhaken, aangezien inspanning een essentieel onderdeel is van de effectiviteit van wenselijke moeilijkheden.

Aangezien gewoontegedrag vaak een voorspeller is van gedrag, onderzocht ik in hoofdstuk 3 de studiegewoonten van universiteitsstudenten en hoe zij nieuwe gewoonten aanleren en bestaande gewoonten afleren om inzicht te krijgen in hoe studenten het gebruik van effectieve leerstrategieën in stand houden. Ik gebruikte een kwalitatieve benadering en nodigde 29 eerstejaarsstudenten uit, die werden verdeeld over zes focusgroepdiscussies, om beter inzicht te krijgen in hun gewoontes rondom studeren en de uitdagingen die gepaard gaan met het integreren van effectieve leerstrategieën. Thematische analyse toonde aan dat de leerstrategiekeuze van studenten vaak werd bepaald door de type toetsing en de ervaren efficiëntie voor het bereiken van kortetermijndoelen. Hoewel studenten enige metacognitieve kennis hadden, werd gedragsverandering beschreven als moeizaam en alleen ondernomen wanneer dat nodig werd geacht, bijvoorbeeld wanneer eerdere leerstrategieën niet hielpen om een tentamen te halen. Andere studenten gaven aan dat ze van plan waren hun studiegedrag te veranderen, maar niet goed wisten hoe. De motivatie fluctueerde gedurende het semester en beïnvloedde of studenten hun veranderingsvoornemens daadwerkelijk uitvoerden. Bovendien had het omgaan met levensuitdagingen, zoals de overgang van de middelbare school naar de universiteit, invloed op het studiegedrag van studenten. De bevindingen bieden inzicht in de factoren die studenten motiveren hun leergedrag te veranderen en benadrukken het belang van afstemming tussen beoordelingsmethoden en langetermijnleren. Daarnaast kan het ondersteunen van studenten bij het formuleren van langetermijndoelen voor hun studie de ontwikkeling van studiegewoonten stimuleren. Dit kan bijdragen aan langdurig leren en een consistente toepassing van effectieve leerstrategieën om deze doelen te bereiken.

Aangezien gebleken is dat het stellen van doelen effectief is om gedragsverandering op andere domeinen in gang te zetten, heb ik in hoofdstuk 4 onderzocht of het stellen van doelen via implementatie-intenties het gebruik van gespreid leren kan vergroten. Daarnaast onderzocht ik het zelfregulerend leren van universiteitsstudenten gedurende een vierwekencursus. Middels de experience sampling method (ESM) heb

ik het dagelijks gebruik van gespreid leren en ander studiegedrag van studenten (N = 85) gemonitord, zoals hun studiemotivatie, inspanning en tevredenheid. Ik vergeleek hoe studiegedrag verschilde tussen studenten die specifieke implementatie-intenties hadden om gespreid leren te integreren (n = 35) en studenten die aan het begin van het onderzoek alleen werden geïnformeerd over de voordelen van gespreid leren en het stellen van doelen (n = 50). Hoewel implementatie-intenties het gebruik van gespreid leren niet verhoogden, gebruikten studenten in deze groep effectievere strategieën, zoals oefentoetsen vroeg in de cursus, studeerden ze korter, rapporteerden ze lagere inspanning en lieten hogere concentratie zien richting het einde van de cursus. Tegelijkertijd behaalden ze vergelijkbare tentamenresultaten als de controlegroep. In beide groepen veranderde het studiegedrag in de loop van de tijd, waarbij de duur van studeersessies, het gebruik van effectieve leerstrategieën, de motivatie, de inspanning en de tevredenheid over de studeersessies toenamen naarmate de tentamens naderden. Kwalitatieve analyse van de implementatie-intenties suggereert dat studenten over het algemeen in staat waren om doelen te formuleren voor het regelmatig herhalen van eerder geleerde stof, maar dat deze doelen vaak niet specifiek en concreet genoeg waren. In het algemeen wijzen de bevindingen erop dat implementatie-intenties weliswaar niet direct leiden tot een toename van het gebruik van gespreid leren, maar wel kunnen bijdragen aan efficiënter studiegedrag, zoals eerder gebruik van retrieval practice. Verder laten de resultaten zien dat het leergedrag van studenten verandert, waarin de nabijheid van tentamens een sterke invloed heeft op hoe studenten hun inspanningen en motivatie verdelen. Deze patronen onderstrepen het belang van het ontwerpen van toetsingsmethoden die consistent leren voor langetermijnbehoud stimuleren in plaats van kortetermijnprestaties. Bovendien illustreert de studie het belang van het onderzoeken van zelfgereguleerde leerprocessen over langere perioden middels ESM om vast te stellen hoe studenten hun studiegedrag dynamisch aanpassen in reactie op veranderende academische eisen.

In hoofdstuk 5 gebruikte ik een vergelijkbaar ontwerp als in hoofdstuk 4, en breidde dit uit door drie groepen te includeren en een follow-up ESM-periode van een week toe te voegen vijf weken na de cursus om mogelijke transfereffecten te onderzoeken. In de implementatie-intentiegroep (N = 29) vormden studenten implementatie-intenties, in de information-only-groep (N = 36) kregen studenten alleen informatie over gespreid leren en de voordelen daarvan, en de controlegroep (N = 35) kreeg geen aanvullende informatie. Gedurende een cursus van vier weken gebruikte ik ESM (k = 1998) om dagelijks studiegedrag vast te leggen, zoals het gebruik van leerstrategieën, studieduur, motivatie en inspanning. Vijf weken later hadden we een follow-up ESM-periode van één week (k = 343) om mogelijke transfereffecten te beoordelen. Net als in hoofdstuk 4 suggereren de resultaten dat het formuleren van implementatie-intenties het gebruik van gespreid leren niet significant verhoogt vergeleken met de controlegroep. In plaats daarvan voorspelden de individuele intenties van studenten om gespreid leren te gebruiken hun daadwerkelijk gebruik van gespreid leren. Veranderingen in studiegedrag over de tijd heen werden

voornamelijk beïnvloed door contextuele factoren, met name de nabijheid van tentamens. Naar mate de tentamens naderden, rapporteerden studenten in alle groepen meer inspanning, studietijd, concentratie, extrinsieke motivatie en tevredenheid, samen met minder afleiding. Ongeacht de groep werd het gebruik van gespreid leren in de volgende cursus voorspeld door het gebruik van gespreid leren tijdens de eerste ESM-periode. Deze resultaten suggereren dat veranderingen in het leergedrag van studenten eerder worden bepaald door de nabijheid van tentamens dan door het stellen van doelen. Verder onderstrepen de bevindingen hoe moeilijk het is om intenties om te zetten in consistente gedragsverandering. Vooral voor complexe strategieën die een langdurige inspanning vereisen, zoals gespreid leren, kunnen onderwijsinterventies effectiever zijn wanneer ze studenten helpen een gewoonte te ontwikkelen die het initiëren van regelmatig studeren bevordert. Bovendien zouden beoordelingsmethoden die langetermijnleren in plaats van kortetermijnprestaties belonen, studenten beter kunnen ondersteunen bij het ontwikkelen van duurzame leergewoontes.

In hoofdstuk 6 heb ik de resultaten en implicaties van de studies samengevat en besproken in relatie tot de onderzoeksvragen van dit proefschrift en de wetenschappelijke literatuur. De bevindingen van dit proefschrift lieten zien dat het gebruik van effectieve strategieën in de loop van de tijd fluctueerde onder de invloed van motivatie, interpretatie van ervaren mentale inspanning tijdens het leren en contextuele druk. Hoewel studenten begrepen welke strategieën effectief zijn, slaagden veel studenten er niet in om deze consequent toe te passen. Dat komt omdat de ervaren inspanning als hoog werd ervaren, de voordelen van het gebruik van effectieve leerstrategieën niet voor alle studenten duidelijk waren en met minder inspannende strategieën op korte termijn prestaties konden worden behaald. Inspanning werd vaak geïnterpreteerd als een teken van slecht leren, wat een belemmering kan vormen voor het toepassen van wenselijke moeilijkheden, die inspanning vereisen. Het ontwikkelen van gewoontes rond effectief studiegedrag bleek complex, mogelijk omdat leerstrategieën zoals gespreid leren meerdere stappen omvatten die moeilijk te automatiseren waren. Het consequent toepassen van strategieën hangt daarom waarschijnlijk niet alleen af van metacognitieve kennis, maar ook van specifieke intenties om ze te gebruiken en van ondersteunende omgevingen. Deze omgevingen kunnen bijvoorbeeld helpen bij het interpreteren van leerinspanningen, het verminderen van de inspanningen nodig om effectieve leerstrategieën toe te passen, en het afstemmen van het nut van effectieve strategieën op de doelen van studenten. Het stimuleren van een consistente toepassing van effectieve leerstrategieën vraagt uiteindelijk om leeromgevingen die inspannend leren normaliseren, passende ondersteuning bieden en beloningsstructuren richten op langetermijnbegrip in plaats van kortetermijnprestaties.

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Deutsche Zusammenfassung

Insbesondere im Hochschulkontext werden Studierende in hohem Maße gefordert, ihr Lernen eigenständig zu planen, zu überwachen und zu steuern – sie müssen ihr Lernen selbstregulieren. Die effektive Nutzung evidenzbasierter Lernstrategien ist dabei eine zentrale Voraussetzung für akademischen Erfolg. Obwohl Studierende zunehmend über metakognitives Wissen hinsichtlich wirksamer Lernstrategien verfügen, wenden viele weiterhin weniger effektive Strategien an. Diese Diskrepanz zwischen Strategiewissen und tatsächlichem Lernverhalten stellt eine zentrale Herausforderung für die Förderung des selbstregulierten Lernens dar. Die Forschung hat verschiedene Barrieren identifiziert, die die beständige Anwendung effektiver Lernstrategien erschweren. Bislang ist jedoch unzureichend geklärt, wie diese Barrieren in authentischen Lernkontexten zusammenwirken und wie Studierende dabei unterstützt werden können, effektive Strategien dauerhaft in ihr Lernverhalten zu integrieren. Um diese Forschungslücke zu schließen, wird in dieser Dissertation untersucht, warum Studierende effektive Lernstrategien nicht konsistent anwenden und inwiefern verhaltensänderungsbezogene Ansätze die beständige Strategienutzung fördern können.

Zur Beantwortung der Forschungsfragen wurden vier Studien durchgeführt. Ausgehend von der Cue-Utilization-Theorie (Koriat, 1997) wurde in Kapitel 2 untersucht, wie wahrgenommene mentale Anstrengung, Überwachungsurteile (z. B. subjektiver Lernerfolg) und tatsächlicher Lernerfolg zusammenhängen. Da Lernende keinen direkten Zugang zu ihrem tatsächlichen Lernerfolg haben, greifen sie auf Hinweisreize (Cues) zurück, um ihren Lernerfolg zu beurteilen. Frühere Befunde legen nahe, dass erhöhte mentale Anstrengung häufig als Indikator für geringeren Lernerfolg interpretiert wird. Mithilfe eines metaanalytischen Strukturgleichungsmodells wurden Daten aus 35 Manuskripten (83 unabhängige Stichproben, 236 Effektgrößen, N = 3973) integriert. Über alle Studien hinweg zeigte sich ein negativer Zusammenhang zwischen wahrgenommener mentaler Anstrengung und Überwachungsurteilen ($\beta = -.19$). Studierende, die höhere Überwachungsurteile berichteten – also stärker das Gefühl hatten, etwas gelernt oder verstanden zu haben – erzielten auch höhere tatsächliche Lernergebnisse ($\beta = .29$). Indirekt ergab sich somit ein negativer Zusammenhang zwischen wahrgenommener Anstrengung und tatsächlichem Lernerfolg ($\beta = -.05$). Dieses Muster deutet darauf hin, dass Lernende Anstrengung häufig als Zeichen ineffektiven Lernens interpretieren. In den untersuchten Kontexten erwies sich die wahrgenommene Anstrengung als diagnostischer Hinweisreiz. Gleichzeitig verdeutlichen die Ergebnisse die Notwendigkeit, Lernende bei der Interpretation von Anstrengung zu unterstützen, insbesondere im Kontext effektiver Lernstrategien, bei denen Anstrengung lernförderlich sein kann.

Da Gewohnheiten als stabiler Prädiktor des Verhaltens gelten, wurde in Kapitel 3 qualitativ untersucht, welche Lerngewohnheiten Studierende aufweisen und wie sie diese entwickeln, verändern oder aufgeben. In sechs Fokusgruppen mit 29 Studierenden wurden habitualisiertes Lernverhalten sowie Erfahrungen mit der Integra-

tion effektiver Lernstrategien untersucht. Die thematische Analyse zeigte, dass die Lernstrategiewahl stark von Prüfungsformaten und kurzfristiger Zielerreichung beeinflusst wurde. Obwohl metakognitives Wissen vorhanden war, wurden Verhaltensänderungen häufig als aufwändig erlebt und meist erst dann umgesetzt, wenn bisherige Strategien nicht mehr zum Bestehen von Prüfungen ausreichten. Motivation erwies sich als dynamisch und kontextabhängig. Zusätzlich beeinflussten Herausforderungen wie der Übergang von der Schule zur Universität das Lernverhalten. Die Befunde unterstreichen die Bedeutung struktureller Rahmenbedingungen. Prüfungsformate und akademische Zielsetzungen sollten stärker auf langfristigen Kompetenzerwerb ausgerichtet werden. Zudem könnte die Förderung langfristiger akademischer Zielsetzungen zur Entwicklung stabiler Lerngewohnheiten beitragen und damit beständiges Lernen sowie die konsequente Nutzung effektiver Lernstrategien unterstützen.

Da sich Zielsetzung in anderen Bereichen als wirksame Methode zur Initiierung von Verhaltensänderungen erwiesen hat, wurde in Kapitel 4 untersucht, ob Zielsetzung mittels Implementierungsintentionen („Wenn–Dann-Pläne“) die Anwendung des verteilten Übens durch Studierende erhöhen kann. Mithilfe der Erlebens-Stichproben-Methode (ESM) wurde während eines vierwöchigen Universitätskurses bei Studierenden (N = 85) die tägliche Anwendung des verteilten Übens sowie weitere Lernverhaltensindikatoren wie Lernmotivation, Lernanstrengung und Lernzufriedenheit erfasst. Verglichen wurde dabei, inwiefern sich diese Variablen zwischen Studierenden, die spezifische Implementierungsintentionen zur Integration des verteilten Übens sowie Hindernispläne (d. h. Pläne zum Umgang mit potenziellen Barrieren; n = 35) formulierten, und Studierenden, die zu Beginn der Studie lediglich über die Vorteile des verteilten Übens und die Zielsetzung informiert wurden (n = 50), unterscheiden. Obwohl Implementierungsintentionen die Anwendung des verteilten Übens nicht erhöhten, zeigten Studierende dieser Gruppe ein effizienteres Lernverhalten. Sie nutzten frühzeitig effektivere Strategien wie Abrufübungen, lernten in kürzeren Zeiteinheiten, berichteten geringere Lernanstrengung und wiesen gegen Ende des Kurses eine erhöhte Konzentration auf, während sie in der Abschlussprüfung vergleichbare Leistungen wie die Kontrollgruppe erzielten. In beiden Gruppen veränderte sich das Lernverhalten im Zeitverlauf. Mit zunehmender Prüfungsnähe nahmen Lernzeit, Einsatz effektiver Lernstrategien, Motivation, Lernanstrengung und Lernzufriedenheit zu. Die qualitative Analyse der Implementierungsintentionen deutet darauf hin, dass die Studierenden grundsätzlich in der Lage waren, Ziele zur regelmäßigen Wiederholung bereits gelernter Inhalte zu formulieren; diese Ziele waren jedoch häufig nicht hinreichend konkret. Insgesamt zeigen die Befunde, dass Implementierungsintentionen die Anwendung des verteilten Übens zwar nicht direkt steigern, jedoch möglicherweise ein effizienteres Lernverhalten unterstützen, etwa durch eine frühzeitigere Nutzung abrufbasierter Strategien. Zudem verdeutlichen die Ergebnisse, dass sich Lernverhalten dynamisch verändert und maßgeblich durch die zeitliche Nähe zu Prüfungen beeinflusst wird, insbesondere hinsichtlich der Al-

lokation von Anstrengung und Motivation. Diese Befunde unterstreichen die Bedeutung von Prüfungs- und Bewertungsformaten, die kontinuierliches Lernen zur langfristigen Wissensspeicherung stärker fördern als kurzfristige Leistung. Darüber hinaus zeigt die Studie den Mehrwert längsschnittlicher Untersuchungen selbstregulierter Lernprozesse mittels ESM, da sich so erfassen lässt, wie Studierende ihr Lernverhalten adaptiv an verändernde akademische Anforderungen anpassen.

In Kapitel 5 wurde ein ähnliches Design wie in Kapitel 4 verwendet und um eine dritte Gruppe sowie eine Nachbeobachtungsphase erweitert, um mögliche Transfereffekte zu untersuchen. In der Gruppe mit Implementierungsintentionen (n = 29) formulierten die Studierenden Wenn-Dann-Pläne, um das verteilte Üben in ihr Lernverhalten einzubauen. In der Informationsgruppe (n = 36) erhielten die Studierenden ausschließlich Informationen über das verteilte Üben und dessen Vorteile, während die Kontrollgruppe (n = 35) keine zusätzliche Intervention erhielt. Über einen Zeitraum von vier Wochen wurde mithilfe von ESM (k = 1.998) das tägliche Lernverhalten erfasst, darunter der Einsatz von Lernstrategien, Lernzeit, Motivation und Lernanstrengung. Fünf Wochen später folgte eine einwöchige ESM-Nachbeobachtungsphase (k = 343), um potenzielle Transferwirkungen des Lernverhaltens und der Zielerreichung auf einen neuen Kurs zu untersuchen. Analog zu Kapitel 4 deuten die Ergebnisse darauf hin, dass die Formulierung von Implementierungsintentionen die Anwendung des verteilten Übens im Vergleich zu den Kontrollbedingungen nicht signifikant erhöhte. Stattdessen sagten die individuellen Intentionen der Studierenden, verteiltes Üben einzusetzen, ihre tatsächliche Anwendung dieser Strategie vorher. Veränderungen im Lernverhalten über die Zeit wurden primär durch kontextuelle Faktoren beeinflusst, insbesondere durch die zeitliche Nähe zu Prüfungen. Gruppenübergreifend berichteten Studierende mit zunehmender Prüfungsnähe von höherer Lernanstrengung, längerer Lernzeit, gesteigerter Konzentration, erhöhter extrinsischer Motivation und größerer Lernzufriedenheit bei gleichzeitig geringerer Ablenkung. Unabhängig von der Gruppenzugehörigkeit wurde die Anwendung des verteilten Übens im Folgekurs durch dessen Nutzung während der Haupt-ESM-Phase vorhergesagt. Diese Befunde legen nahe, dass Veränderungen im Lernverhalten stärker durch Prüfungsnähe als durch Zielsetzung beeinflusst werden, und verdeutlichen die Schwierigkeit, Intentionen in konsistente Verhaltensänderungen zu überführen. Insbesondere bei komplexen Strategien wie dem verteilten Üben, die über längere Zeiträume hinweg kontinuierliche Anstrengung erfordern, könnten Interventionen wirksamer sein, wenn sie Studierende dabei unterstützen, eine Initiierungsgewohnheit zu etablieren, die den regelmäßigen Lernbeginn fördert. Darüber hinaus könnten Prüfungs- und Bewertungsformate, die langfristiges Lernen statt kurzfristiger Leistung belohnen, Studierende besser bei der Entwicklung stabiler Gewohnheiten des selbstregulierten Lernens unterstützen.

In Kapitel 6 werden die Ergebnisse und Implikationen der Studien zusammengefasst und im Licht der Forschungsfragen dieser Dissertation sowie der relevanten Fachliteratur diskutiert. Die Ergebnisse zeigen, dass die Anwendung effektiver Lern-

strategien im Studienverlauf schwankt und von motivationalen, metakognitiven und kontextuellen Faktoren beeinflusst wird. Obwohl Studierende über Strategiewissen verfügen, scheitert die konsequente Umsetzung häufig an wahrgenommener Anstrengung, kurzfristigen Anreizstrukturen, und motivationalen Schwankungen. Wahrgenommene Anstrengung wurde häufig als Indikator für ineffektives Lernen interpretiert, was die Benutzung effektiver Lernstrategien erschweren kann. Die Etablierung beständiger Lerngewohnheiten erwies sich insbesondere bei komplexen Strategien wie dem verteilten Üben als herausfordernd. Die Befunde dieser Dissertation legen nahe, dass die beständige Strategienutzung nicht allein durch metakognitives Wissen gefördert werden kann. Vielmehr sind konkrete Handlungsintentionen, strukturelle Unterstützung, adaptive Anstrengungsinterpretation sowie Anreizsysteme erforderlich, die langfristiges Wissen statt kurzfristiger Leistung belohnen. Die Förderung selbstregulierten Lernens erfordert somit Lernumgebungen, die Anstrengung normalisieren, Lernstrategieanwendung erleichtern und langfristige Lernziele systematisch unterstützen.

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Appendices

Declaration of Use of Generative AI

Ackowledgements

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Declaration of Use of Generative AI

I have used the generative AI (GenAI) tool ChatGPT (models 4.0 and 5.1) during the writing process of this dissertation. I used the software to support language editing and to improve the readability (e.g., clarity, structure, wording, and organization) of the chapters. More specifically, I used it to edit and improve the clarity of text that I drafted myself by sharing sections of my own writing and asking for help with language accuracy, refining sentences, strengthening tone, or reducing redundancy. I also used it to help rephrase parts of my own text to avoid self-plagiarism. I did this by sharing sections of my writing and asking ChatGPT to compare them with each other and indicate self-plagiarism, and asking it for alternative formulation suggestions. I occasionally asked for transition sentences to improve the flow between paragraphs. I did this by sharing the paragraphs I had written. Sometimes, I also shared sections of my writing or gave a brief summary thereof to ask for suggestions for section headings, theme headings (Chapter 3), or titles.

By doing this, GenAI influenced how I presented my work, but it did not influence the ideas, reasoning, interpretations, or conclusions of this dissertation. Using GenAI to improve my writing enabled me to increase the quality of my writing in an efficient manner and provided me with additional feedback. Furthermore, it increased my general skills of engaging with GenAI (output). Reviewing all generated content critically and verifying it before including it in this dissertation helped me to improve my academic writing skills while allowing me to take full ownership and responsibility of this dissertation.

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About the Author

Louise David completed her Bachelor's degree in Psychology at Maastricht University. After her bachelor's, she undertook a six-month internship at Volkswagen AG in Wolfsburg, Germany, where she supported employees' workplace learning and development. This experience strengthened her interest in understanding how learning can be effectively supported across contexts.

She subsequently enrolled in a Research Master's programme in Behavioural Sciences at Radboud University in Nijmegen, the Netherlands. Her master's thesis focused on the unpleasantness of mental effort, laying the foundation for her doctoral research.

In late 2021, Louise started her PhD at Maastricht University, where she examined the sustainable use of effective learning strategies in higher education. Alongside her doctoral research, she was actively involved in teaching, mentoring, and educational development. Toward the end of her PhD, she joined the Study Smart project team, where she contributed to the further development and implementation of Study Smart, a research-informed training programme aimed at optimizing university students' use of effective learning strategies. She obtained her University Teaching Qualification (UTQ) and is certified as a competence coach.

Currently, Louise continues her work as a postdoctoral researcher at Maastricht University, where she further investigates how university students can be supported in adopting and sustaining effective learning strategies within their authentic learning contexts.