# Psychological Factors and Mechanisms of Digital Learning

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The digital environment is different from natural and social environments. Technologies are evolving to support new methods of collaborative learning and interaction. A key challenge is to ensure that technology-enhanced education is effective and creates a supportive environment for students. This requires considering adaptive motivations, emotions, and psychological factors such as intrinsic motivation, cognitive load and self-regulation, all which influence student engagement and success in digital learning.

This chapter provides an overview of literature on psychological processes important in digital learning. Factors such as motivation, cognitive management, and self-regulation shape student performance in these environments. The psychology of digital learning explores the cognitive, emotional, and social dimensions of education in the digital age. Research aims to optimize these environments for better learning outcomes. Understanding these psychological elements is essential for educators to create more effective, engaging, and enjoyable digital learning experiences, though the field is still developing, and many aspects remain to be explored.

*Keywords:* digital learning, intrinsic motivation, cognitive load, self-regulation, technology-enhanced education


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## Introduction

Digital technology presents new learning opportunities and is now a dominant mode of education (Wang et al., 2024). Emerging digital media foster learner autonomy but demand efficient regulation of the learning process for sustained academic progress. Understanding psychological factors, like cognitive load, motivation, and self-regulation, is vital for improving educational outcomes (Edisherashvili et al., 2022). As digital education evolves, supporting self-regulated learning (SRL) becomes crucial for academic success.

This chapter reviews studies to highlight how these interconnected psychological dimensions influence digital learning, aiming to optimize experiences and address challenges unique to online environments.

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## Self-Regulation and Metacognition

Students in digital environments must regulate their learning through time management, goal setting, and self-monitoring. Strong self-regulation skills are essential for managing time, setting goals, and tracking progress. Metacognitive strategies like planning, monitoring, evaluating, self-assessment, and reflection support learners in staying on track and improving performance (Pintrich, 2002; Schraw & Moshman, 1995). These skills are crucial for successful digital learning. While self-regulation and metacognition are closely related, they are distinct concepts in cognitive science and educational psychology, each playing a unique role in the learning process.

### *Self-Regulated Learning*

Self-regulated learning (SRL) is a key competence of successful learning in digital learning environments, and it is a dynamic process characterized by the active participation of learners. including the cognitive, metacognitive, behavioral, motivational, and emotional/affective aspects of learning (Panadero, 2017). It is often referred to as the driving competence needed for transforming individuals into successful independent learners (Boekaerts, 1991). SRL requires learners' active participation, i.e., they need to activate cognitive and metacognitive learning strategies and to be aware of their prior knowledge and skills (Broadbent, 2017).

Previous studies in digital educational settings (Yilmaz et al., 2020; Bui et al., 2022) suggest that those who can effectively monitor and regulate their cognition, motivation and behavior are more likely to engage in deeper learning and achieve greater academic success than learners with weaker self-regulation skills (Carter et al., 2020). Self-regulated learners could plan their learning, set goals and acquire new knowledge independently (Theobald, 2021).

SRL has been widely investigated by different authors within last three decades to determine how behavioral, motivational, and cognitive components interact, and several models for SRL have been developed. For further reading, see Panadero (2017) overview of models of SRL. However, what the various existing models of SRL have in common is its cyclical process with several phases and areas that are partly overlapping. Panadero (2017) highlighted a three-phase structure identified by Puustinen and Pulkkinen (2001): *Preparation, Performance, and Appraisal*. While these phases may be labeled differently across models, they are consistently present. Based on meta-analytic evidence from existing SRL models, Panadero (2017) draws two key conclusions. First, SRL models offer a broad and cohesive framework that aids in teaching students to be more strategic and efficient learners. Second, the effectiveness of these models depends on the students' developmental stages or educational levels. Thus, researchers and educators must take these differences into account when utilizing SRL models and theories to enhance students' learning outcomes and self-regulation abilities.

However, findings from studies involving higher education students and workplace trainees (Sitzmann & Ely, 2011) indicate that the four strongest predictors – *goal setting, persistence, effort, and self-efficacy* – hold considerable motivational significance and are all encompassed within socio-cognitive theory. These findings are consistent with those of Richardson and colleagues (2012), who identified that (a) self-efficacy is the strongest predictor, (b) goal-setting strategies enhance effort regulation, and (c) comprehensive interventions tend to be more effective. Consequently, it appears that interventions targeting motivational and emotional aspects, such as self-efficacy and goal setting, tend to yield better outcomes for higher education students.

The article by Zeitlhofer et al. (2023) provides practical advice on enhancing learning performance in digital learning environments through the strategic use of prompts. One key recommendation is to *incorporate cognitive prompts* that encourage learners to focus on important information, identify relationships, and organize content, thus improving comprehension and retention of knowledge. The authors also suggest the use of *metacognitive prompts* to foster self-reflection, planning, and monitoring of the learning process, guiding learners in evaluating their understanding and adapting their strategies accordingly. It is important to *balance the frequency of prompts*; they should be provided at appropriate intervals to support learning without causing interruptions. Too frequent prompts can overwhelm learners, while too sparse prompts may not offer sufficient support. Additionally, prompts should be *customized based on individual learner needs*, optimizing their effectiveness by catering to learners at various stages of their learning journey. Lastly, the authors (Zeitlhofer et al., 2023) advise using *interactive digital tools* that allow for engagement with prompts. These tools can track progress and provide adaptive feedback, further enhancing the learning process in digital environments. In summary, the article emphasizes that cognitive and metacognitive prompts, when strategically implemented, can significantly improve learning outcomes in digital settings.

### *Metacognition*

Metacognition encompasses the processes through which individuals assess their own understanding and adapt their learning strategies accordingly, improving problem-solving and decision-making. Metacognition is defined as 'thinking about thinking' or the ability to monitor and control one's cognitive processes (Dunlosky & Metcalfe, 2008) and comprises both the ability to be aware of one's cognitive processes (metacognitive knowledge) and to regulate them (metacognitive control) (Fleur et al., 2021). Metacognition plays an important role in learning and education (Pintrich, 2002). By fostering metacognitive skills, learners become more effective in planning, monitoring, and evaluating their cognitive activities, which enhances their overall academic performance.

In the field of educational sciences, there is extensive research on metacognitive training, but we lack a solid understanding of what methods are most effective and why. While some studies suggest that enhancing metacognitive skills improves academic performance (Dignath et al., 2008), other interventions show inconsistent results (Jacob & Parkinson, 2015; Kassai et al., 2019), and there remains limited understanding of their long-term impact or transfer effects. So, there is still a need to establish clear links between metacognition in the brain and its application in areas such as education. Furthermore, educational and cognitive neuroscientists explore metacognition in different contexts and using different methods. While cognitive neuroscientists often examine metacognition through behavioral tasks (such as Flanker tasks, Stroop task...), educational researchers tend to rely primarily on introspective, self-report questionnaires or interviews (Dinsmore et al., 2008). It remains uncertain to what degree these differing approaches to measuring metacognition align and represent the same underlying processes. Gaining a deeper understanding of the cognitive processes that underpin metacognition and their representation in the brain could offer valuable insights into these aspects. In recent years, there has been a lot of progress in brain research, studying the neural mechanisms of metacognition (Vaccaro & Fleming, 2018), and starting to orient itself towards training metacognitive abilities that would translate into real-life benefits, yet it is unclear at this point how these results may inform educational sciences or interventions.

In cognitive neuroscience, metacognition research follows two paths: one explores meta-knowledge, focusing on the neural basis of introspective judgments about one's own cognition (i.e., metacognitive judgements), and meta-control with experiments involving cognitive offloading (e.g., subjects can perform actions such as set reminders, making notes and delegating tasks) (Risko & Gilbert, 2016; Gilbert et al. 2020), while the other investigates executive functions (EF), also referred to as cognitive control (Fernandez-Duque et al., 2000), which is closely related to metacognition.

However, it is important for researchers and practitioners to know how to improve learning in digital environments. Braad and colleagues (2022) focus their research on the importance of metacognitive support in SRL and investigated a detached approach in which digital metacognitive support is provided in parallel to ongoing domain-specific training via a digital tool. The results suggest that students should be encouraged to assess and improve their metacognitive skills, increase their metacognitive knowledge and improve their metacognitive skills. Types of support include direct instruction on how to use metacognitive strategies effectively, metacognitive scaffolding (like using virtual characters to guide learners), and metacognitive prompts that remind students to self-monitor and regulate their learning process. The results also indicated that, while students with higher metacognition found a lack of relevance of using the tool, students with lower metacognition are less likely to make (structural) use of the available support. A key challenge for future research is thus to adapt metacognitive support to learner needs, and to provide metacognitive support to those who would benefit from it the most. Devers et al. (2018) emphasize using instructional support to improve SRL and metacognition. This support includes strategies such as direct teaching of metacognitive processes and providing environments that limit distractions. They point out that teacher expectations and feedback can significantly impact students' ability to self-regulate

## Motivation

One of the key factors contributing to the success of digital learning is the student's motivation. Motivation to learn is a key psychological concept in education and one of the most important factors determining success in different learning environments, including digital ones, that drives students to engage in learning (Hartnett, 2016; Faridah et al., 2020; Berestova et al., 2022).

In digital learning environment, cognitive motivation, which involves motivation for conscious action, plays a crucial role (De Leeuw et al., 2019). In addition, in a digital environment, where learners experience more autonomy and flexibility, intrinsic motivators such as curiosity, personal achievement, and self-determination play a key role in their success (Hsu et al., 2019). Learners must often rely on intrinsic motivation because the absence of face-to-face interaction can reduce external motivators, such as direct praise from instructors or peer pressure. Some studies (e.g. Soffer & Nachmias, 2018) reinforce the idea that well-designed digital learning platforms, with rich interactive content, are key to engaging learners and fostering intrinsic motivation. Typically, digital learning is externally regulated, meaning that many students tend to complete assignments driven primarily by extrinsic motivation. Without adequate educator support that emphasizes the value of e-learning, there is a risk that students' motivation may decline into amotivation, as their online learning experiences may lack sufficient motivational regulation (Fryer & Bovee, 2016).

To increase learner motivation and engagement in both traditional and digital environments, Keller's ARCS model (Keller, 1987) is widely used in instructional design. From the perspective of digital learning (Keller, 2009), the 'A' in Keller's ARCS model stands for '*Attention*', which emphasizes the importance of creating an engaging and attractive online or technology-enhanced environment. This involves considering the design elements, interactivity, and presentation formats that capture and sustain learners' attention and curiosity. The visual appeal and interactive nature of digital platforms play a key role in drawing learners in and keeping them motivated throughout the learning process. The 'R' stands for '*Relevance*', which involves ensuring that the content is meaningful and applicable to learners' goals, needs, and interests. In digital learning, this means creating content that connects with learners' prior knowledge, future aspirations, or personal interests, and making it clear how the material will benefit them in real-world situations. By aligning content with the learners' objectives, digital platforms can maintain their engagement and motivation throughout the learning process. The 'C' stands for '*Confidence*', which refers to ensuring that learners feel capable of successfully completing the tasks or mastering the content. In digital learning, this involves designing activities and providing feedback that build learners' belief in their own abilities. When learners are gradually challenged in ways that match their skill level and receive positive reinforcement, they develop the confidence needed to persist and succeed in their learning journey. The 'S' stands for '*Satisfaction*', which refers to ensuring that learners feel a sense of accomplishment and reward after completing tasks or learning activities. In digital learning, this can be achieved through positive feedback, recognition of achievements, and offering opportunities for learners to apply what they've learned in meaningful ways. By ensuring learners feel satisfied with their progress and outcomes, digital platforms help sustain their motivation and encourage continued engagement with the material. In digital learning, the satisfaction that learners experience is crucial for sustaining motivation and engagement.

Recent studies emphasize that satisfaction in digital environments often comes from a combination of well-designed technological platforms, interactive elements, and emotional engagement (Li et al., 2023). For example, a study published in 2024 (Yin et al., 2024) revealed that learning satisfaction is not merely driven by a student's adoption of new learning technology, but also by a range of cognitive and emotional attributes that reflect the user's positive perception of and engagement within the system. In other words, students with a positive attitude toward technology are more likely to perceive the design intentions for fostering advanced thinking, actively communicate and collaborate with peers, and emotionally invest in the learning process. These affirmative experiences, in turn, result in higher satisfaction with the digital learning experience. In digital and e-learning environments, students' satisfaction significantly improves due to the perceived ease of access, intuitive navigation, interactivity, and user-friendly interface design, especially when compared to traditional education methods (De Leeuw et al., 2019). Overall, several factors can influence students' satisfaction with learning and, in turn, their motivation to achieve better outcomes. These factors include feedback, progress, and internal rewards. Students' perceptions of satisfaction may vary based on prior experiences, technological familiarity, and individual preferences (Faridah et al., 2020).

Various motivational theories, such as self-determination theory (SDT) (Ryan & Deci, 2020), expectancy-value theory (Wigfield & Eccles, 2000), achievement goal theory (Senko et al., 2011), and control-value theory (Pekrun et al., 2017), have been widely applied to understand factors that boost students' learning and engagement. These theories examine how environmental and psychological factors influence motivation and learning. While effective in traditional settings (Lazowski & Hulleman, 2016), there has been limited exploration of how these theories can be adapted to enhance online learning and engagement in technology-driven environments (Chiu, 2021; Hsu et al., 2019).

Despite the limited focus on adapting motivation theories for digital contexts, learner motivation remains a key factor for successful SRL, which is presented in the previous section. As a reference discussing the importance of learners' motivation in SRL within digital learning, Artino (2008) explores how motivation plays a critical role in digital environments, highlighting the interaction between motivational beliefs and the use of self-regulatory strategies in online learning contexts.

For conclusion, to foster motivation in digital learning, educators can implement strategies such as personalized learning pathways, gamification elements, and interactive content that actively engages students (Huang et al., 2020). Gamification elements, such as point systems, badges, and leaderboards, can increase student engagement by introducing a sense of achievement and competition. Providing timely and constructive feedback, along with opportunities for social interaction and collaboration, can enhance students' sense of autonomy and competence, reinforcing intrinsic motivation (Deci & Ryan, 2000). Integrating social components, such as collaborative learning, discussion forums, and virtual study groups, which promote a sense of belonging and social connection. This social presence can positively influence motivation and long-term engagement in digital learning. Timely and personalized feedback is also essential when students receive immediate, specific feedback tailored to their progress, they are more likely to stay motivated and persist in their learning efforts. Additionally, incorporating real-world applications and goal-setting techniques helps learners see the relevance of their studies, increasing their persistence and overall engagement in digital environments (Pintrich, 2003). By incorporating these strategies, digital learning environments can better support student motivation, ensuring sustained interest and improved learning outcomes.

## Cognitive Load and Information Processing

Cognitive load and information processing are important psychological factors in digital learning. Given the rapid development of digital learning, it is important to advance the understanding of cognitive load theory (CLT) in line with this growing body of research (Skulmowski & Xu, 2022).

In cognitive psychology, cognitive load refers to the amount of working memory resources used. Cognitive load can be understood as the mental effort required to process and retain information, which is limited by the constraints of working memory. Effective instructional design aims to manage these cognitive demands to optimize learning and prevent cognitive overload, and CLT describes the different categories of load that can occupy their memory capacity (Sweller et al., 1998). CLT suggests that excessive information can overwhelm a learner's working memory, thereby reducing their ability to learn effectively. The central focus of CLT categorizes the demands on working memory into three types*:* intrinsic cognitive load (ICL), extraneous cognitive load (ECL), and germane cognitive load (GCL) (Sweller et al., 1998). Intrinsic cognitive load is the effort associated with understanding a specific topic, extraneous cognitive load relates to how information or tasks are presented, and germane cognitive load involves the effort put into creating a permanent store of knowledge (Sweller et al., 2019). However, over the years, the additive nature of these types of cognitive load has been examined and questioned. It is now believed that they influence each other in a more circular manner.

Recent research (Skulmowski & Xu, 2022; *Orru & Longo, 2019;* Januchta et al., 2022) emphasizes that cognitive load and information processing are crucial factors in digital learning environments. The latest studies expand on CLT by refining its model to better fit the complexities of digital learning settings, highlighting ICL, ECL, and GCL as key components to consider. ICL relates to the complexity of the learning material itself and varies depending on the learner's level of expertise. Recent studies suggest that while ICL cannot be modified through instructional design, it can be managed by gradually increasing complexity and matching content to the learner's prior knowledge (Skulmowski & Xu, 2022). In addition, ECL arises mainly from how information is presented, including poorly designed digital tools that may clutter the interface with irrelevant elements. Reducing extraneous load by streamlining design and focusing on essential information is critical to freeing up cognitive resources for deeper learning (Januchta et al., 2022). Moreover, GCL refers to the cognitive resources devoted to processing and integrating new knowledge into long-term memory. Recent work emphasizes that reducing extraneous load creates more cognitive capacity for germane processes, thereby fostering deeper learning (Skulmowski & Xu, 2022).

Overall, these findings stress the importance of optimizing the design of digital learning environments to balance cognitive load. Digital platforms often present learners with vast amounts of information, which can overwhelm their working memory if not managed effectively. Inappropriate instructional formats can increase extraneous cognitive load, making it harder for students to learn (Abeysekera et al., 2024). Simplifying interfaces, focusing on essential content, and supporting learners with tools that align with cognitive processing principles can significantly enhance information retention and learning outcomes. To further support teachers in optimizing digital learning environments, adaptive learning technologies that personalize content based on individual learners' progress and performance can be implemented. These technologies adjust the difficulty and pacing of learning tasks to match students' cognitive capacities, thereby reducing cognitive overload. Studies, such as by Dziuban et al. (2016), indicate that adaptive learning environments can align with students' cognitive capacities, enhancing learning efficiency.

## Attention and Engagement

Attention plays a crucial role in processing information and retaining knowledge, and the ability to focus attention effectively is directly linked to better learning outcomes and memory retention (Chun et al., 2011). Numerous studies in cognitive psychology have shown that humans have a limited capacity for sustained attention, allowing them to focus on a specific task for only a finite period (Oberauer, 2019). This capacity is flexible and can change based on factors such as the task's complexity and individual aspects like interest, motivation, and experience.

However, the rapid proliferation of digital tools, including smartphones and social media, has introduced new difficulties in maintaining prolonged focus, making constant distraction more accessible than ever. Maintaining attention in digital learning environments is challenging due to potential distractions like social media, constant notifications, multitasking, and the flexible nature of online formats. According to research by the Coalition for Psychology in Schools and Education (2020), strategies such as limiting distractions, using interactive elements, and promoting active engagement can help improve learning retention. These approaches emphasize the importance of creating a focused and engaging online learning environment for students.

Research indicates that the digital environment introduces challenges for maintaining sustained focus due to the constant influx of stimuli, including messages, alerts, and digital interruptions. This phenomenon, known as '*continuous partial attention*', can lead to superficial understanding and decreased ability to concentrate (Kirjakovski, 2023). 'Continuous partial attention' describes the ongoing process of dividing and shifting focus between multiple tasks or stimuli without fully engaging in any of them. This practice often results in a shallow understanding of information and diminished concentration on any single task. As noted by Firth et al. (2019), we have moved from the 'information age' into an 'age of interruption.' This phenomenon, identified by Stone (2007), is a symptom of attentional overload, which occurs when environmental demands exceed an individual's available attentional resources. In the digital world, this overload is driven by a constant stream of stimuli, such as alerts, personalized notifications, social media updates, emails, texts, and news feeds, all vying for our attention. Moreover, frequent interruptions in digital settings, such as checking smartphones or engaging with social media, can overload attentional capacity, impacting cognitive performance and learning outcomes. Studies (Shanmugasundaram & Tamilarasu, 2023) show that excessive use of smartphones and multitasking are linked to poorer attentional control, making it difficult for learners to maintain focus on their tasks.

### *Engagement, Interactive Methods and Microlearning: Practical Approaches for Maintaining Attention in Digital Learning Environments*

Engagement through interactive learning methods, such as quizzes, polls, and gamified elements, plays a crucial role in enhancing learning outcomes in digital environments. These methods help transform passive learning into an active process, as they require learners to actively participate, apply knowledge, and receive immediate feedback (Dichev & Dicheva, 2017). For instance, quizzes can serve as knowledge checkpoints, allowing students to assess their understanding and identify areas for improvement. Similarly, polls and interactive discussions encourage active reflection and help maintain focus by involving learners directly in the material. The use of gamification has been shown to increase not just short-term engagement but also long-term retention by making learning experiences more enjoyable and rewarding (Hamari et al., 2014). Gamified elements, like points, badges, and leaderboards, further boost motivation and engagement by incorporating elements of competition and reward. This approach taps into intrinsic motivators, encouraging learners to remain attentive and committed to the learning process.

*Microlearning* is another highly effective strategy for maintaining attention and enhancing retention in digital environments. By breaking content into smaller, focused lessons, microlearning minimizes cognitive overload, which can occur when learners are exposed to large amounts of information at once (Hug & Friesen, 2007). Short, targeted lessons align with the natural attention span of learners, making it easier for them to absorb and retain key concepts. This approach supports spaced repetition, a method proven to enhance long-term memory by revisiting information at intervals (Smolen et al., 2016).

To summarize, both interactive methods and microlearning provide practical approaches for maintaining attention in digital learning environments. By promoting active engagement and managing cognitive load, these strategies foster a more effective and sustainable learning process.

## Conclusion

In conclusion, the reviewed studies emphasize that digital learning environments require effective support for self-regulation, motivation, and metacognition to enhance educational outcomes. Self-regulated learning (SRL) and metacognitive strategies are critical for managing the learning process, while motivation significantly impacts learners' engagement and success. Optimizing cognitive load through proper instructional design and balancing attention through interactive methods and microlearning can further enhance learning effectiveness. Overall, tailored interventions that consider individual learner needs are vital for supporting sustainable academic progress in digital settings.

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## Psihološki dejavniki in mehanizmi digitalnega učenja

Digitalno okolje se razlikuje od naravnega in družbenega okolja. Tehnologije se razvijajo in podpirajo nove metode sodelovalnega učenja ter interakcij. Ključni izziv je zagotoviti, da bo izobraževanje, podprto s tehnologijo, učinkovito in bo ustvarjalo spodbudno okolje za učence. Pri tem je treba upoštevati motivacijo, čustva in psihološke dejavnike, kot so notranja motivacija, kognitivna obremenitev in samoregulacija, ki vplivajo na vključenost in uspešnost učencev pri digitalnem učenju.

To poglavje vsebuje pregled literature o psiholoških procesih, pomembnih za digitalno učenje. Dejavniki, kot so motivacija, upravljanje kognitivnih procesov in samoregulacija, oblikujejo uspešnost učencev v teh okoljih. Psihologija digitalnega učenja raziskuje kognitivne, čustvene in socialne razsežnosti izobraževanja v digitalni dobi. Cilj raziskav je optimizirati ta okolja za boljše učne rezultate. Razumevanje teh psiholoških elementov je ključnega pomena za izobraževalce, da ustvarijo učinkovitejše, zanimivejše in prijetnejše digitalne učne izkušnje, čeprav se področje še vedno razvija in je treba raziskati še veliko vidikov.

*Ključne besede:* digitalno učenje, intrinzična motivacija, kognitivna obremenitev, samoregulacija, tehnološko podprto izobraževanje