COGNITIVE AND CONTEXTUAL DIMENSIONS OF SELF-REGULATED LEARNING IN AI-DRIVEN DIGITAL CLASSROOMS

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ABSTRACT

The integration of artificial intelligence (AI) in education has significantly reshaped learning environments, demanding higher levels of autonomy and self-regulation from students in digital classrooms. This study explores the cognitive and contextual dimensions of self-regulated learning (SRL) among pre-service cosmetology and beauty teachers at Universitas Negeri Padang, Indonesia. Utilizing a quantitative descriptive design, data were collected from 82 participants through a structured questionnaire covering nine SRL indicators: time management, goal setting, resource access, help-seeking, attentional control, environmental regulation, persistence, knowledge application, and task consistency. Descriptive statistical analysis revealed generally high SRL levels. Contextual aspects, particularly selecting conducive learning environments (M = 4.34) and maintaining task consistency (M = 4.06), showed the highest scores. Cognitive aspects such as accessing digital resources (M = 4.10) and applying ideas in discussions (M = 3.93) were also well developed. However, lower mean scores in time management (M = 3.67) and persistence with less engaging content (M = 3.89) indicate challenges in motivational and behavioral regulation. These findings underscore the need to incorporate SRL-enhancing strategies into AI-driven learning systems and suggest future research should further investigate the emotional and motivational facets of SRL in technology-mediated learning contexts.

Keywords : *Self-Regulated Learning, Artificial Intelligence, Digital Learning, Cognitive Regulation, Contextual Learning*

INTRODUCTION

The rapid expansion of artificial intelligence (AI) technologies in education has redefined the way student access, process, and apply knowledge in digital classrooms. Learning environments have shifted from teacher-centered delivery to personalized and adaptive systems that require students to take greater responsibility for their own learning trajectories (Luckin et al., 2016). As these AI-driven platforms afford greater autonomy and flexibility, they also demand a higher level of self-regulated learning (SRL) competencies—skills essential for managing time, motivation, resources, and cognitive engagement independently (Zimmerman, 2002; Panadero, 2017).

Despite the potential of AI to transform learning experiences, various studies have pointed out a critical paradox: while digital learning systems increase access and per-sonalization, many students struggle to maintain focus, motivation, and structured learning habits in such open-ended environments (Broadbent, 2017; Dabbagh & Kitsantas, 2012). This issue becomes particularly pressing in the Indonesian higher ed-ucation context, where the sudden transition to digital learning—accelerated by the COVID-19 pandemic—has exposed gaps in students' readiness for autonomous learn-ing. A national survey by Pusdatin Kemendikbudristek (2021) revealed that over 58% of university students in Indonesia reported difficulties with self-discipline and consistent study routines in online settings.

Self-regulated learning is widely recognized as a multidimensional construct en-compassing cognitive, metacognitive, behavioral, and contextual dimensions (Pintrich, 2000). In AI-driven learning environments, these dimensions become more pronounced as learners interact with intelligent systems that recommend content, track perfor-mance, and adapt to their learning behavior. However, the success of such systems hinges not only on technological sophistication but also on the learner's capacity to engage actively and consistently with the digital content provided (Azevedo et al., 2010).

Previous studies have examined SRL in digital contexts, with findings suggesting that while students often show strength in goal-setting and resource access, they struggle with sustained focus, self-monitoring, and persistence (Lee & Tsai, 2011; Ki-zilcec et al., 2017). Moreover, cultural and institutional factors, such as passive learning habits and dependence on instructors, may hinder the development of SRL in certain educational systems, including Indonesia's (Marpaung & Pratama, 2022). This under-scores the need to examine SRL not only from a cognitive lens but also from a contextual perspective that includes students' behavioral patterns and their interaction with the learning environment.

Given this background, it becomes crucial to investigate how students in Indone-sia—particularly those in teacher education programs—are navigating the demands of AI-driven digital learning. Pre-service mathematics teachers are of special interest due to the cognitive complexity of their discipline and the expectation for them to develop strong autonomous learning habits that they will later model in their classrooms. However, there is limited empirical evidence mapping their SRL profiles in digital contexts infused with AI technologies.

Thus, this study aims to provide a descriptive analysis of the cognitive and con-textual dimensions of self-regulated learning among cosmetology and beauty students at Universitas Negeri Padang. By identifying strengths and areas of concern in their SRL practices, this research seeks to inform the design of more effective AI-supported learning environments and contribute to the pedagogical preparation of future educa-tors in Indonesia.

METHOD

This study employed a quantitative descriptive research design aimed at capturing the patterns and tendencies of self-regulated learning (SRL) among students in the context of AI-driven digital classrooms. The descriptive approach was selected to pro-vide a comprehensive overview of students' cognitive and contextual SRL practices without manipulating variables, thus reflecting real-world behaviors and perceptions.

The participants of this study were 82 undergraduate students enrolled in the Cosmetology and beauty study program at Universitas Negeri Padang, Indonesia. These students were selected using purposive sampling, based on their active involvement in digital learning environments during the academic year 2024/2025. The participants represent a cohort of pre-service teachers who are expected to develop strong SRL skills both for academic success and future instructional practices.

Data were collected using a self-report questionnaire adapted from validated SRL measurement tools (Pintrich, 2000; Zimmerman, 2002), which had been modified to suit the context of AI-assisted digital learning. The instrument comprised 9 indicators of SRL, representing both cognitive and contextual dimensions:

SRL1: Time management in the absence of scheduled classes
SRL2: Short-term and long-term goal setting
SRL3: Access to online learning resources
SRL4: Seeking help from peers
SRL5: Maintaining focus despite distractions
SRL6: Choosing conducive learning environments
SRL7: Learning persistence despite uninteresting content
SRL8: Application of ideas from readings in academic discussions
SRL9: Consistency in reading and completing assignments

Each item was rated on a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire was distributed digitally through Google Forms to ensure accessibility and convenience for participants engaged in remote and hybrid learning environments. Prior to the data collection, informed consent was obtained, and participants were assured of anonymity and the voluntary nature of their participation.

Descriptive statistical analysis was conducted using SPSS to calculate measures of central tendency (mean, median, mode), dispersion (standard deviation), and range (minimum and maximum values) for each SRL indicator. The analysis focused on identifying dominant SRL behaviors, variations in learning strategies, and potential gaps in self-regulation within the digital learning context.

RESULTS AND DISCUSSIONS

The figure 1 presents the results of a quantitative descriptive analysis of Self-Regulated Learning (SRL) data collected from 82 Cosmetology and beauty students at Universitas Negeri Padang. Furthermore, figure 2 describes the average level of student's self-regulated learning.

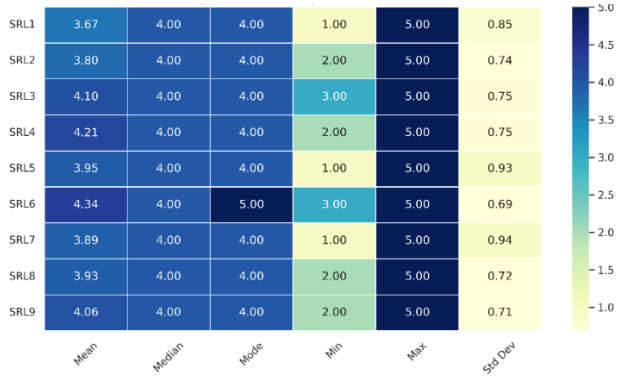


Figure 1. Heatmap statistic of Self-Regulated Learning

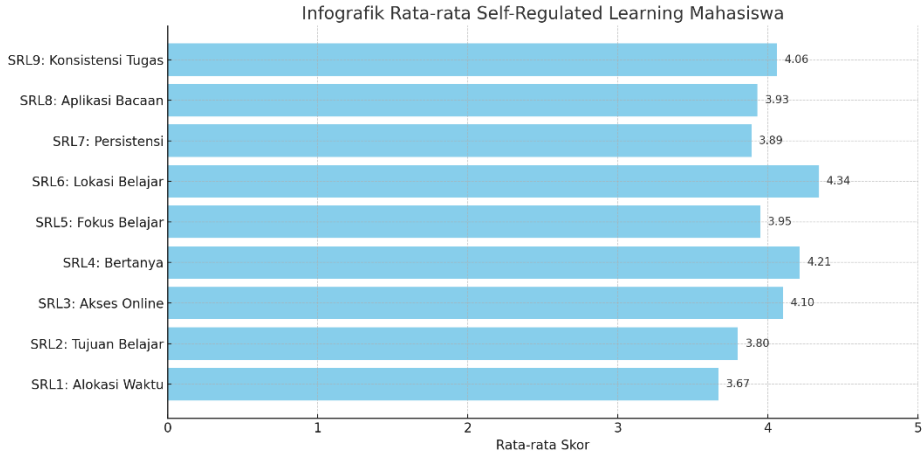


Figure 2. Average level of student's self-regulated learning

The rapid advancement of digital transformation, marked by the integration of ar-tificial intelligence (AI) in education, requires students not only to be proficient in ab-sorbing academic content but also to be competent in independently managing their own learning processes. The descriptive analysis of 82 Cosmetology and beauty stu-dents from Universitas Negeri Padang reveals noteworthy dynamics regarding their Self-Regulated Learning (SRL) competencies.

Time Management and Learning Goals: Foundational Pillars of Self-Regulation

The findings of this study reveal that SRL1 (routine time allocation for studying) recorded the lowest mean score among all SRL indicators, at 3.67. In contrast, SRL2 (setting short- and long-term learning goals) received a slightly higher average score of 3.80. These results suggest that while most students demonstrate an awareness of set-ting learning directions, they still face challenges in consistently managing their study time independently.

In AI-driven learning environments, the ability to autonomously manage study time becomes increasingly critical. Adaptive learning systems such as intelligent tu-toring systems and AI-based learning recommenders offer high flexibility in terms of time and access to learning resources. However, this flexibility also demands stronger self-regulatory capacities from learners (Luckin et al., 2016). As structural pressures like fixed class schedules are reduced, the responsibility of managing

learning time shifts entirely to the students. This aligns with Bandura's Social Cognitive Theory (1986), which posits that self-regulation arises from the interaction between personal factors (motivation, goals), environmental supports (technology), and behaviors (actual learn-ing strategies). Failure in time management reflects a suboptimal development of be-havioral self-regulation.

These findings are consistent with Azevedo and Cromley (2004), who found that while students in hypermedia environments could articulate learning goals, they fre-quently struggled with time and strategy management. Similarly, Broadbent and Poon (2015) demonstrated that time management was a significant predictor of academic success in online learning settings, yet remains a commonly neglected area among students. Research by Zheng et al. (2020) confirmed that students in AI-based learning sys-tems showed improved learning outcomes only when possessing adequate self-regulation skills, particularly in study scheduling. This is reinforced by Gašević et al. (2017), who emphasized that the flexibility of online learning must be accompanied by scaffolding mechanisms that promote explicit goal-setting and time management.

The relatively higher score in goal-setting (SRL2) reflects students' cognitive awareness regarding their learning trajectory. This aligns with Schunk's (2012) assertion that goal-setting is closely related to increased motivation and cognitive monitoring within SRL. Panadero et al. (2017) also supported this view, finding that students with clearly defined learning goals tend to organize their strategies more effectively and ex-hibit greater resistance to distraction.

However, the gap between goal awareness and time management implementation underscores the multidimensional and complex nature of self-regulation. As Zimmer-man (2002) argued, SRL is not only about knowing what to do but also about consist-ently executing it through the cyclical process of forethought, performance control, and self-reflection. Thus, additional support through AI-assisted self-monitoring tools is needed—tools that not only provide content but also offer reminders, alerts, and per-sonalized analytics on time-use effectiveness.

These findings highlight the need for AI-based learning platforms to go beyond content delivery and actively support students' self-regulatory skills. Digital platforms should incorporate features such as goal-setting modules, calendar planning, and learning analytics dashboards to help students visualize their progress and maintain consistency in study routines. Pedagogical interventions—such as time management workshops and guided learning reflection—are also recommended, particularly at the beginning of the academic term as part of digital learning orientation.

Access and Utilization of Digital Learning Resources

The mean score for SRL3 (accessing online learning resources relevant to course-work) was 4.10, indicating a strong tendency among students to independently seek information beyond formal instructional materials. This reflects a key indicator that students have developed learning behaviors aligned with 21st-century educational demands, particularly in leveraging technology and artificial intelligence in academic contexts.

Within the framework of Constructivist Learning Theory (Vygotsky, 1978), learning through the exploration of digital resources exemplifies an active approach to con-structing knowledge. Students are no longer dependent solely on lecturers as the pri-mary source of information; instead, they proactively engage with digital content to derive meaning. Furthermore, Cognitive Flexibility Theory (Spiro et al., 1987) suggests that the diversity of digital media and learning resources enables

students to under-stand concepts from multiple perspectives, thereby enhancing deep comprehension and knowledge transfer.

This finding aligns with the study by Lee and Tsai (2011), which demonstrated a positive correlation between the use of online learning resources and self-regulated learning strategies, particularly in the domain of resource management. In AI-driven learning environments, students increasingly rely on platforms that offer adaptive content, interest-based learning recommendations, and personalized automated guid-ance. Research by Ifenthaler and Yau (2020) further supports this perspective, showing that students who regularly access digital learning resources experience enhanced en-gagement, especially when these resources are curated or supported by AI systems. Their study also highlighted the importance of perceived usefulness of technology as a motivational factor influencing access frequency.

Similarly, Papamitsiou and Economides (2014) explored the role of learning ana-lytics in shaping students' learning strategies, concluding that students who receive feedback on their progress and learning needs from AI-based systems are more likely to actively seek and utilize supplementary resources. Wang, Wu, and Wang (2009) reinforced this argument by showing that students' perceptions of the ease of use and relevance of digital content significantly influenced their intention to continuously access online learning materials independently.

In the Indonesian context, research by Pratama and Firmansyah (2022) revealed that students who habitually utilize digital platforms such as Google Scholar, educa-tional YouTube channels, and even AI-based chatbots (e.g., ChatGPT) exhibit more in-dependent and reflective learning strategies compared to those who rely solely on materials provided by lecturers. These findings underscore that strengthening digital literacy is no longer option-al—it is an essential requirement. Students must be continuously supported in access-ing digital resources that are not only valid but also integrated into their individual learning pathways. Higher education institutions can develop AI-integrated learning dashboards that not only present content but also recommend materials based on stu-dents' individual weaknesses and interests.

Moreover, instructors are encouraged to adopt flipped classroom and project-based learning strategies that prompt students to independently seek references as part of the learning process. Such approaches reinforce the self-regulation cycle—from planning to reflection.

Social Regulation in Collaborative Learning

The mean score for SRL4 was 4.21—one of the highest in this study—indicating a strong tendency among students to seek help from peers when encountering learning difficulties. In the context of self-regulated learning (SRL), this strategy falls under help-seeking, a metacognitive process that reflects self-awareness of comprehension limitations and a readiness to access relevant assistance (Zimmerman, 2002).

This phenomenon highlights that SRL is not a purely individualistic process but inherently involves a strong social dimension. Vygotsky's Sociocultural Theory (1978) emphasizes that social interaction is a foundational component of cognitive develop-ment. In the context of digital and AI-supported learning, virtual collaboration and knowledge exchange through online forums, discussion groups, or chat features within Learning Management Systems (LMS) expand the opportunities for productive social regulation.

Research by Hadwin, Järvelä, and Miller (2018) identifies socially shared regulation of learning (SSRL) as an advanced form of SRL, wherein regulatory processes are dy-namically

distributed within group interactions. The findings of this study confirm that students have begun to develop SSRL, particularly in the form of collaborative help-seeking. Wise and Cui (2018) found that AI-powered discussion forums, which highlight and prioritize critical student questions, enhance both the quality and frequency of student inquiries. This suggests that even in online and automated learning environ-ments, collaborative dimensions can be effectively supported through technolo-gy-enhanced systems.

Similarly, Koedinger et al. (2015), in their study on AI-based learning dashboards, revealed that features displaying peer activity and progress foster academic social in-teraction. Students are more inclined to seek clarification from peers who demonstrate high performance, as indicated by AI-generated metrics. Moreover, AI-driven peer matching, as explored by Holstein et al. (2019), allows digital learning systems to automatically recommend discussion partners based on cognitive profiles and learning styles, thereby reinforcing the function of social regula-tion within the digital ecosystem.

Local research by Suryani and Rahmatika (2021) supports these findings, reporting that Indonesian students show a strong preference for discussing digital content diffi-culties with classmates via WhatsApp groups, Telegram, or institutional e-learning platforms. From a theoretical perspective, Transactional Distance Theory (Moore, 1993) posits that in distance learning systems, increased learner-to-learner interaction reduces per-ceived transactional distance. Social interactions—such as asking questions to peers—serve as strategies to bridge the gap between students and both content and instructors in online learning environments.

These findings emphasize that AI-driven digital learning should not eliminate opportunities for social interaction. Learning platforms should be intentionally de-signed to facilitate peer interaction, AI-facilitated discussion boards, and collaborative tagging systems. Instructors should also incorporate collaborative tasks that encourage knowledge exchange and normalize help-seeking as a legitimate academic strategy. Higher education institutions can further support this process by developing AI-based collaboration recommendation systems that group students based on their cognitive strengths and weaknesses. In this way, social regulation becomes not only an organic outcome but also a systematically facilitated process.

Self-Regulation through Environmental Control, Focus, and Learning Resilience

Three indicators represent the dimension of students' self-regulation in addressing both internal and external challenges commonly encountered in digital learning envi-ronments: SRL5 (effort to remain focused despite distractions) with a mean score of 3.95, SRL6 (selection of low-distraction learning environments) with the highest score of 4.34, and SRL7 (persistence in learning despite boring material) with a score of 3.89.

These indicators reflect students' self-regulatory capacities in managing both ex-ternal and internal learning conditions, as well as their academic resilience. In the highly open and often unstructured context of digital learning, students' ability to control their attention and persevere under suboptimal learning circumstances is a key determinant of academic success.

According to Pintrich's Metacognitive Self-Regulation Theory (2000), strategies for managing attention, monitoring distractions, and establishing optimal learning condi-tions are critical components of the self-regulated learning (SRL) process. The ability to select low-distraction environments (SRL6) suggests that students have developed awareness of external factors influencing their focus. The high mean score of 4.34 for SRL6 indicates that environmental regulation has become

a major concern for stu-dents—aligned with findings by You (2016), who identified learning environment management as a significant predictor of success in AI-based online courses.

The capacity to maintain focus in the presence of distractions (SRL5) reflects the component of attentional control. In the digital era, this skill is particularly vital as students must filter an overload of information and notifications. Rukavina and Daneman (1996) emphasized that attentional control requires intensive metacognitive training, especially in highly distracting environments. Research by Louwrens and Hartnett (2015) further demonstrated that students employing attentional regulation strategies are more consistent in completing self-paced learning activities on LMS platforms.

Moreover, the score for SRL7 reflects learning resilience—students' ability to en-dure cognitive and affective challenges. Datu and Yang (2021) identified academic re-silience as a crucial mediator between intrinsic motivation and learning success in AI-based learning platforms. Even in adaptive systems where content is personalized, students still require perseverance and emotional endurance to engage with less en-gaging material.

This finding is corroborated by Broadbent (2017), who observed that students with high SRL scores maintain persistence even when the learning content does not fully align with their interests. The primary implication of these findings is the need for the development of AI-driven study planners and adaptive nudging systems that not only deliver content but also recommend optimal study times, locations, and methods based on students' individual learning habits. Higher education institutions should also support the inte-gration of distraction-control features—such as focus modes or notification re-strictions—within digital learning applications.

Strengthening Higher-Order Cognition through Knowledge Transfer and Aca-demic Consistency

The following two indicators highlight self-regulatory aspects focused on infor-mation processing and the application of knowledge in academic contexts: SRL8 (ap-plying ideas from readings into class discussions), with a mean score of 3.93, and SRL9 (maintaining consistency in reading and completing assignments), with a score of 4.06. These indicators reflect students' cognitive maturity and academic consisten-cy—namely, the ability not only to comprehend information but also to critically apply it and sustain task completion over time. In the context of AI-based learning, these skills are essential, as content is often personalized and demands active application rather than passive consumption.

According to the Theory of Transfer of Learning (Perkins & Salomon, 1992), the ability to apply knowledge in new contexts requires deep engagement, reflection, and the formation of conceptual connections. The relatively high SRL8 score indicates stu-dents' ability to transfer ideas into academic discourse. This finding is supported by De Corte (2012), who emphasized that learning systems promoting cognitive trans-fer—such as interactive discussions and integrated projects—enhance conceptual un-derstanding.

SRL9 reflects students' sustained efforts in reading and task completion. A study by Tempelaar et al. (2015) in the field of learning analytics found that students with consistent engagement profiles tend to achieve higher academic outcomes compared to those with sporadic learning patterns. This is closely linked to Cognitive Load Theory (Sweller, 1988), which posits that consistent learning enables optimal cognitive pro-cessing, thereby improving comprehension and long-term retention. Research by Kizilcec, Pérez-Sanagustín, and Maldonado (2017) on AI-powered MOOCs also revealed that

students who engage consistently are more likely to com-plete the course compared to those with irregular study behaviors.

In the Indonesian context, a study by Irwansyah and Sari (2023) found that students who habitually articulated ideas from their readings in online discussion forums demonstrated higher levels of understanding on essay-based assessments—indicating successful cognitive transfer and metacognitive reflection. AI-based curriculum designers and instructors should incorporate learning activi-ties that promote knowledge transfer, such as case-based learning, problem-based learning, or simulation-based tasks within digital platforms. Additionally, AI systems should integrate auto-feedback tools and reflective journaling modules to encourage students to consistently evaluate their understanding and academic progress.

CONCLUSIONS

This study provides a descriptive overview of the cognitive and contextual di-mensions of self-regulated learning (SRL) among cosmetology and beauty students at Universitas Negeri Padang within the context of AI-driven digital classrooms. The findings indicate that while students exhibit strong tendencies in areas such as access-ing online resources, choosing effective learning environments, and completing aca-demic tasks consistently, challenges remain in maintaining focus during distraction, scheduling study time independently, and sustaining motivation when learning mate-rials are less engaging.

High mean scores in indicators like environmental regulation (SRL6) and task completion (SRL9) suggest that students are becoming increasingly competent in managing external learning conditions and academic demands. Meanwhile, moderate scores in goal setting (SRL2) and persistence (SRL7) highlight areas for development in internal motivational control and learning resilience. These results reinforce the need for integrating SRL scaffolding into AI-based educational platforms to support learners not only cognitively but also emotionally and behaviorally.

Limitations of the Study and Future Research

Several limitations should be acknowledged in interpreting the findings of this study. First, the research relied on self-reported data, which may be subject to social desirability bias or inaccuracies in self-assessment. Second, the sample was limited to a single institution and one academic program, which may restrict the generalizability of the results to other disciplines or educational contexts. Third, the descriptive quantita-tive design did not allow for deeper causal inferences or exploration of individual learner trajectories over time. Additionally, this study focused solely on cognitive and contextual dimensions of SRL, without incorporating emotional or motivational com-ponents in detail, which are also critical in the AI-supported learning process.

Future research should consider employing mixed-methods approaches to explore not only how students regulate their learning but also why certain SRL behaviors emerge in digital settings. Longitudinal studies could track the development of SRL competencies over time and assess the impact of specific AI-based tools or interven-tions. Expanding the study across multiple institutions and diverse fields of study would enhance the representativeness and provide comparative insights. Researchers should also consider examining affective and motivational dimensions of SRL using real-time data from AI learning platforms, such as emotion detection, engagement analytics, or behavior tracking, to gain a holistic understanding of student regulation in AI-driven environments. Lastly,

collaboration with system developers and instructional designers could support the creation of SRL-enhancing features within AI-based learning systems, en-suring that technology serves not only as content delivery but also as a metacognitive support system.

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