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The Self-Regulation for AI-Based Learning Scale: Psychometric Properties and Validation

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Abstract

Artificial intelligence technologies are transforming university students' learning processes, making self-regulation skills increasingly crucial. However, existing self-regulation scales inadequately reflect AI-assisted learning environments' unique dynamics. This study developed the Self-Regulation for AI-Based Learning Scale (SRAILS) for university students and examined its psychometric properties. The scale comprises four main dimensions and nine sub-dimensions: motivational components (intrinsic/extrinsic motivation, self-efficacy), cognitive/metacognitive strategies, time and task management, resource management, and technological adaptation. The study included 750 university students from various Turkish faculties. Exploratory Factor Analysis supported construct validity, while Confirmatory Factor Analysis confirmed the nine-factor structure, demonstrating good model fit. Convergent and discriminant validity were established. Cronbach's alpha and McDonald's omega reliability coefficients ranged from .853-.913. Criterion-related validity was confirmed through significant positive correlations between all scale dimensions and external criteria: academic GPA, technology interest, and digital literacy levels ($r = .20$-$.60$, $p < .01$). SRAILS provides a comprehensive, reliable assessment of students' self-regulation skills in AI-assisted learning environments. This scale contributes originally to literature by enabling personalized learning experience design and supporting effective instructional strategy development.

Keywords: Artificial intelligence in education, Psychometric validation, Scale development, Self-regulated learning, University students.

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Introduction

The rapid proliferation of artificial intelligence (AI) technologies in education fundamentally transforms learning processes in higher education. In recent years, there has been a notable increase in university students' frequency of using AI tools for educational purposes, including ChatGPT, Grammarly, AI-based note-taking applications, intelligent content recommendation systems, and personalized learning platforms (Balcı, 2024; Jo, 2024; Sublime & Renna, 2024). This technological transformation has increased students' reliance on AI-assisted tools in their academic work and has also revealed the need for new competencies in learning processes (Zawacki-Richter et al., 2022). Such developments suggest a shifting paradigm in which students must adapt to new tools and ways of thinking, evaluating, and interacting with knowledge. Understanding how students engage with AI and develop the necessary self-regulatory skills becomes increasingly important in this context. However, it is also important to acknowledge the potential pedagogical risks of AI-based learning environments, such as cognitive laziness, reduced critical thinking effort, or overdependence on automated systems (Ahmad et al., 2023; Gerlich, 2025; Jose et al., 2025; Sharma, 2024; Zhai et al., 2024). Therefore, a balanced approach that fosters the effective use of AI tools and the cultivation of essential cognitive and metacognitive skills is crucial to ensure meaningful and independent learning in higher education.

In AI-assisted learning environments, students' possession of self-regulation skills is critically important for effectively utilizing these technologies (Dahri et al., 2024). Self-regulated learning (SRL) is a multifaceted process encompassing an individual's cognitive, motivational, behavioral, and affective control over their learning process (Zimmerman, 2000). In AI-assisted learning, students need these skills to set learning goals independently, strategically use AI tools, monitor progress, and implement necessary strategies. However, students' ability to benefit from AI tools varies depending on their digital literacy, metacognitive awareness, and motivational resources—which are all critical for effective self-regulated learning in technology-rich environments (Jin et al., 2025; Lan & Zhou, 2025; Qi et al., 2025; Wang et al., 2025; Xiao et al., 2024). Current literature reveals that university students primarily use AI tools for academic purposes such as completing assignments, editing writing, conducting research, and summarizing content (Ravšelj et al., 2025; Xu, 2025). Nevertheless, there are significant differences in AI usage approaches among students. While some students use these technologies only for superficial information gathering or quick results—representing low-level cognitive purposes (Balabdaoui et al., 2024; Fu & Hiniker, 2025; Yang et al., 2024)—others utilize AI more strategically in deep learning processes. These usage patterns are closely linked to students' self-regulation capacities, which shape how they engage with AI and sustain its effective use over time (Diao et al., 2024; Setälä et al., 2025; Tang et al., 2024; Zhai et al., 2023). Therefore, measuring self-regulation skills in AI-based learning environments is critical for understanding individual differences and designing compelling learning experiences.

Although there are studies in the literature that use AI to support students' self-regulation skills (Guan et al., 2025; Naznin et al., 2025; Wu & Chiu, 2025), there is limited research measuring students' self-regulation skills in AI-assisted learning processes (Jin et al., 2025; Wang et al., 2025). Existing measurement instruments are typically developed for traditional learning environments and do not reflect the unique dynamics of AI-assisted learning. This situation creates a significant gap in comprehensively evaluating students' learning competencies in the AI era. To address this gap, the present study has two main goals: (1) to develop the Self-Regulation for AI-Based Learning Scale (SRAILS) for university students and (2) to examine its psychometric properties.

The developed scale aims to comprehensively assess students' motivational, cognitive-metacognitive, behavioral, and environmental regulation skills in AI-assisted learning. Through this instrument, researchers and instructional designers can systematically evaluate students' learning competencies in the AI era, enabling the design of more effective AI-assisted learning environments. Additionally, the scale will contribute to identifying individual differences and informing the development of personalized instructional strategies in AI-supported educational contexts.

Theoretical Framework

Artificial intelligence (AI)--assisted learning environments fundamentally transform traditional learning processes by providing students with personalized content, adaptive guidance, and real-time feedback. To optimally benefit from these dynamic and technologically rich environments, students critically depend on possessing self-regulatory learning skills. Self-regulation is an active learning approach encompassing individuals' competencies in strategically planning, systematically monitoring, effectively controlling, and evaluating their learning processes (Zimmerman, 2002).

Self-regulatory learning in AI-assisted environments is conceptualized through four fundamental components: motivational components, cognitive strategies, task management, and resource management (Pintrich & Garcia, 1994; Pintrich, 2000; Zimmerman & Schunk, 2011). These dimensions preserve the robust foundations of classical self-regulation theories while simultaneously reflecting the unique requirements of digital-age learning environments. The first dimension encompasses motivational components that drive students toward AI-assisted learning processes. Drawing from Pintrich's (2000) self-regulatory learning model and Bandura's (1997) self-efficacy concept within social cognitive theory, this dimension is structured through three sub-dimensions. In AI-assisted learning, intrinsic motivation is characterized by individuals' natural desire to discover new knowledge using artificial intelligence tools, the inherent pleasure derived from this process, and increased curiosity drive. On the other hand, extrinsic motivation is shaped by expectations that AI usage will contribute to academic success, social approval, and future career advantages. The self-efficacy dimension reflects students' beliefs in their ability to use AI tools effectively, cope with challenges encountered in this process, and work independently.

The second fundamental dimension addresses students' competencies in acquiring, processing, organizing information, and managing learning processes at a metacognitive level within AI-assisted environments. This dimension draws from Pintrich and Garcia's (1994) cognitive strategies classification and Zimmerman's (2002) metacognitive self-regulation model. AI-assisted cognitive strategies encompass students' abilities to summarize content, create visualizations, establish connections between concepts, and engage in interactive exercises using artificial intelligence tools (Black & Tomlinson, 2025; Hutapea et al., 2024; Nguyen et al., 2024). Recent studies have shown that students frequently use large language models like ChatGPT to condense and clarify course materials. For instance, in a study of Vietnamese undergraduates, 58.9% of students reported using ChatGPT to summarize lesson content quickly (Nguyen et al., 2024), while another study found that 83.3% of students found AI-generated summaries understandable, and 70% reported enhanced efficiency and confidence when reading academic texts with AI assistance (Hutapea et al., 2024). Similarly, students use AI to map conceptual relationships and visualize topic structures, as evidenced by student reflections in a writing course (Black & Tomlinson, 2025). Building upon these cognitive strategies, metacognitive self-regulation includes competencies in critical thinking, information verification, developing alternative approaches, and continuous evaluation during AI-assisted learning processes. Recent findings suggest that AI tools support these skills by enabling students to quiz themselves, evaluate their understanding, and explore conceptual alternatives (Black & Tomlinson, 2025; Labadze et al., 2023). This dimension particularly emphasizes skills in questioning AI-generated content, evaluating from different perspectives, and comparing with reliable sources.

The third dimension measures how systematically and efficiently students manage time and academic tasks in AI-assisted learning processes. This dimension is structured based on the time management dimension of the MSLQ (Motivated Strategies for Learning Questionnaire) and Zimmerman and Schunk's (2011) task commitment studies. AI-assisted time management refers to students' abilities to plan study programs using artificial intelligence tools, adhere to predetermined time frames, and efficiently organize the process. The task management dimension encompasses competencies in prioritizing tasks, maintaining focus, controlling attention, and acting systematically to achieve goals during AI-assisted learning processes. Given that AI-assisted learning systems typically have asynchronous and flexible structures, this dimension plays a determining role in student success (Jin et al., 2025; Lan & Zhou, 2025).

Table 1. Theoretical Framework Summary

Dimension	Sub-dimension	Theoretical Foundation / Source
1. Motivational Components	1.1 Intrinsic Motivation toward AI-Based Learning 1.2 Extrinsic Motivation toward AI-Based Learning 1.3 Self-Efficacy	Pintrich (2000) – Goal orientation, motivation Bandura (1997) – Social cognitive theory, self-efficacy MSLQ – Motivational components
2. Cognitive and Metacognitive Strategies	2.1 AI-Assisted Cognitive Strategies 2.2 Metacognitive Self-Regulation	Pintrich & Garcia (1994) – Cognitive strategies Zimmerman (2002); Pintrich (2000) – Metacognitive processes
3. Time and Study Management	3.1 AI-Assisted Time Management 3.2 Task Management	MSLQ – Time management dimension Zimmerman & Schunk (2011) – Task commitment, planning
4. Environmental Self-Regulation	4.1 Resource Management for AI Usage 4.2 Technological Adaptation and Flexibility	Pintrich (2000); MSLQ – Resource regulation 21st century skills, digital literacy (Lai & Bower, 2019; Van Laar et al., 2017)

The final dimension addresses competencies specific to the dynamic nature of AI-assisted learning environments.

The theoretical foundation of this dimension is constructed by expanding from Pintrich's (2000) resource regulation concept through 21st-century skills and digital literacy literature (Lai & Bower, 2019; Van Laar et al., 2017). Resource management for AI usage encompasses students' abilities to select appropriate resources when working with artificial intelligence tools, conduct reliability assessments, compare different sources, and develop information verification habits. Technological adaptation and flexibility refer to students' openness to learning new AI tools, rapid adaptation to technological changes, development of alternative solutions to technical problems, and competency in discovering different learning methods.

This multidimensional approach reconceptualizes traditional components of self-regulatory learning by the requirements of AI-assisted learning environments. Each dimension represents different competency areas necessary for students to utilize artificial intelligence technologies effectively and interact with others to form a holistic self-regulation profile (see Table 1). Consequently, the scale developed based on this theoretical framework aims to comprehensively evaluate university students' self-regulatory skills in AI-assisted learning processes. It is grounded in both the robust foundations of classical learning theories and the dynamic requirements of contemporary digital learning reality.

Literature Review

The increasing integration of artificial intelligence technologies in higher education necessitates a deeper understanding of how students can effectively regulate their learning processes within these technologically enhanced environments. Self-regulated learning skills have consistently demonstrated strong associations with academic success, as students who systematically set goals, plan their work, monitor progress, and adapt strategies tend to achieve higher performance, deeper understanding, and greater adaptability in new learning contexts (Grueneke et al., 2024). This relationship becomes even more critical in AI-supported learning environments, where learners must autonomously manage complex information flows and sophisticated learning tools while actively monitoring and controlling their cognition, motivation, behavior, and environment.

Recent research indicates that AI tools, including chatbots and adaptive tutors, possess significant potential to support the forethought, performance, and reflection phases of self-regulated learning (Lan & Zhou, 2025). When AI tools are designed to be easily accessible and user-friendly, they can substantially enhance students' self-regulation capabilities, subsequently improving their higher-order thinking skills (Zhou et al., 2024). Effective self-regulation enables students to capitalize on AI features such as personalized feedback and adaptive content delivery, enhancing their critical thinking and problem-solving abilities. However, without adequate self-regulatory skills, learners may struggle to leverage the potential benefits of AI-assisted learning environments fully.

The consequences of self-regulation deficits in AI tool utilization are particularly concerning. Research demonstrates that when students lack sufficient self-regulatory skills, their engagement with AI tools often remains suboptimal and superficial. Unguided learners frequently underutilize AI capabilities, tapping only basic functions while ignoring more sophisticated adaptive features that could significantly enhance their learning experience (Klar, 2025). Conversely, students with well-developed self-regulatory strategies tend to engage more deeply and strategically with AI tools, using them for planning, elaboration, and self-testing activities that result in higher-quality learning interactions. The quality of AI-generated feedback, particularly from tools like ChatGPT, has been found to depend significantly on learners' goal-setting and self-regulation strategies, suggesting that students with stronger self-regulatory skills are more capable of eliciting useful and meaningful responses from AI systems (Wu et al., 2025).

Furthermore, learners with weaker self-regulation may develop problematic dependencies on AI "shortcuts," engaging in excessive cognitive offloading that neglects active problem-solving processes. This over-reliance on AI technologies risks undermining student engagement and self-efficacy, potentially creating a counterproductive learning dynamic (Lan & Zhou, 2025). Research suggests that adaptive instructional approaches, such as embedding AI tools within collaborative group work contexts, can more effectively develop self-regulatory skills than independent AI usage (Wu et al., 2025).

Despite the apparent importance of self-regulation in AI-supported learning contexts, current measurement approaches reveal significant limitations. No self-regulation scale has been specifically designed for AI-enhanced learning environments. Instead, researchers have relied on established instruments such as Zimmerman's self-regulation model or the Motivated Strategies for Learning Questionnaire (MSLQ), which measures dimensions including resource management, motivational beliefs, metacognitive knowledge, and cognitive engagement (Wang et al., 2025). While these general-purpose instruments have provided valuable insights, they were not developed with AI assistance in mind and may not adequately capture how learners regulate their interactions with AI tools.

Several critical self-regulatory skill domains have emerged as relevant in AI learning contexts. Metacognitive processes, including planning, monitoring, and evaluating one's own learning, are consistently identified as fundamental. Self-regulated learners can initiate cognitive and metacognitive processes, establish clear goals, plan tasks systematically, and continuously monitor and reflect on their progress (Grueneke et al., 2024). Motivational regulation and goal orientation are essential, as maintaining interest and self-efficacy keeps learners engaged when utilizing AI tools. Adequate time and resource management skills also enable successful learners to manage their study time efficiently and seek appropriate help or resources as needed. Educational chatbots have been found to support students in locating information, selecting appropriate strategies, and monitoring understanding, although they often provide limited support for goal-setting and reflection activities (Guan et al., 2025). These findings highlight that effective self-regulation in AI-assisted learning relies on a dynamic interplay between cognitive, metacognitive, motivational, and behavioral dimensions.

The literature reveals a notable gap in our understanding of self-regulation within AI-enhanced learning contexts. No validated instrument currently exists specifically for measuring self-regulatory learning in AI-supported environments, and few empirical studies have directly examined how varying levels of self-regulation affect students' utilization of generative AI tools (Wang et al., 2025; Zhou et al., 2024). Researchers have called for deeper investigation into how AI can support or inadvertently hinder self-regulatory and metacognitive development (Lan & Zhou, 2025).

Addressing these research gaps holds significant implications for educational practice and theory. A more precise understanding of the interplay between self-regulation and AI utilization would guide the design of learning environments and interventions that foster student autonomy and critical thinking. Knowing which self-regulatory skills most strongly predict effective AI tool use could inform scaffolding strategies, such as teaching students how to craft effective prompts or engage in meaningful reflection on AI-generated responses. Moreover, developing assessment instruments designed explicitly for self-regulation in AI contexts would enable systematic monitoring and personalized support for learners.

Given these considerations, the current study addresses this critical gap by developing and validating the Self-Regulation for AI-Based Learning Scale (SRAILS) for university students. This instrument aims to provide researchers and educational practitioners with a reliable tool for measuring students' self-regulatory competencies in AI-assisted learning environments, thereby enabling more effective design and implementation of AI-enhanced educational experiences. Through this comprehensive measurement approach, the study contributes to understanding individual differences in AI-assisted learning processes and supporting the development of personalized instructional strategies that optimize the potential of artificial intelligence in higher education.

Method

Participants

The present study was conducted with a final sample of 750 university students in various faculties across different cities in Türkiye. Before determining the final dataset, a three-step data screening process was carried out to ensure the quality and reliability of responses collected via Google Forms. First, 14 duplicate responses (based on identical IP addresses and response patterns) were identified and removed. Second, 23 participants who completed the questionnaire in less than 10 minutes than the estimated minimum time required to complete all items thoughtfully were excluded from the dataset. Third, among the remaining responses, 32 participants were identified as having failed to respond correctly to embedded attention-check items (e.g., "Please select "Sometimes"' for this item to show you are paying attention") and were also excluded from the analysis. As a result, 750 valid responses were retained for final analysis. The distribution of participants based on their descriptive characteristics is presented in Table 2.

Table 2. Participant Demographics and AI-Related Characteristics (N = 750)

Category	Subcategory	n	%
Faculty	Engineering	162	21.6
	Education	150	20.0
	Arts and Sciences	138	18.4
	Economics & Admin. Sciences	123	16.4
	Communication	84	11.2
	Fine Arts	48	6.4
	Sport Sciences	45	6.0
Gender	Male	410	54.6

	Female	338	45.1
	Prefer not to say	2	.3
Academic Year	1st year	178	23.7
	2nd year	185	24.6
	3rd year	154	20.5
	4th year	233	31.1
AI Familiarity Duration	Less than 6 months	47	6.3
	6 months – 1 year	149	19.9
	1–2 years	282	37.6
	More than 2 years	272	36.2
Daily AI Usage Duration	< 30 minutes	409	54.5
	30–60 minutes	261	34.8
	1–2 hours	63	8.4
	> 2 hours	17	2.3
Most Frequently Used AI Tools[1]	ChatGPT	472	62.9
	Gemini	224	29.9
	Grok	77	1.3
	Stable Diffusion	58	7.7
	GitHub Copilot	41	5.5
	DALL·E	36	4.8
	Claude	32	4.3
	Midjourney	30	4.0
	Other	42	5.6
Purpose of AI Use[2]	Assignment/project assistance	510	68.0
	Information research	450	60.0
	Summarizing lecture notes	413	55.1
	Writing assistance	375	50.0
	Exam preparation	345	46.0
	Entertainment	315	42.0
	Translation or writing in foreign language	285	38.0
	Curiosity/experimentation	263	35.1
	Planning/organizing daily life	165	22.0
	Coding/debugging	135	18.0

[1] Multiple-response item; percentages reflect proportion of total respondents selecting each option.

[2] Participants could select more than one purpose; percentages indicate frequency per option, not cumulative total.

Instrument

To assess university students' self-regulatory capacities in AI-based learning contexts, a new measurement tool entitled The Self-Regulation for AI-Based Learning Scale (SRAILS) was developed. The scale was grounded in prominent theoretical models of self-regulated learning, particularly those advanced by Pintrich (2000), Bandura (1997), Zimmerman (2002), and based on established instruments such as the Motivated Strategies for Learning Questionnaire (MSLQ). These models emphasize the interplay between motivational, cognitive, metacognitive, behavioral, and contextual factors in students' learning regulation processes. The scale development was also informed by contemporary perspectives on digital literacy and 21st-century learning competencies (Lai & Bower, 2019; Van Laar et al., 2017).

The scale structure was built upon a theoretical framework consisting of four main dimensions, each comprising two sub-dimensions, reflecting the multifaceted nature of self-regulated learning in AI-supported environments:

- Motivational Components (Pintrich, 2000; Bandura, 1997; MSLQ)
  - Intrinsic Motivation toward AI-Based Learning
  - Extrinsic Motivation toward AI-Based Learning
  - Self-Efficacy
- Cognitive and Metacognitive Strategies (Pintrich & Garcia, 1994; Zimmerman, 2002)
  - AI-Assisted Cognitive Strategies
  - Metacognitive Self-Regulation
- Time and Study Management (Zimmerman & Schunk, 2011; MSLQ)
  - AI-Assisted Time Management
  - Task Management
- Environmental Self-Regulation (Lai & Bower, 2019; Pintrich, 2000; Van Laar et al., 2017)
  - Resource Management for AI Usage
  - Technological Adaptation and Flexibility

The initial item pool consisted of 90 items, with 10 items for each sub-dimension, developed based on an extensive review of the relevant literature (e.g., Lai & Bower, 2019; Pintrich, 2000; Van Laar et al., 2017; Zimmerman, 2002; Wang et al., 2025). During item development, particular attention was paid to adapting content from existing validated self-regulation instruments (e.g., MSLQ) while tailoring items to the unique demands of AI-based learning environments.

All items were structured using a 5-point Likert-type scale (1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Often, 5 = Always), allowing for nuanced assessment of the frequency of students' self-regulatory behaviors in digital and AI-integrated learning contexts. The scale was designed to measure a broad spectrum of self-regulation strategies essential for navigating AI-enhanced educational settings, including motivation, cognitive control, time management, and adaptability to technological resources.

Procedures

Initially, expert opinions were obtained from two specialists with doctoral degrees in educational sciences to ensure the content and face validity of the item pool. Both experts hold PhDs in curriculum and instruction, with expertise in curriculum development and instructional design and extensive experience in educational assessment. The experts reviewed content coverage, clarity, and appropriateness for the construct. Based on their evaluations, items with overlapping or similar meanings were removed to reduce redundancy and streamline the scale. Both experts agreed that the remaining items had sufficient face validity. Item retention varied across subscales based on theoretical considerations and content validity requirements. Self-efficacy retained four items as experts determined this number was sufficient to capture the unidimensional construct effectively. In comparison, Metacognition required seven items to adequately represent its multifaceted nature encompassing planning, monitoring, and evaluation processes: theoretical frameworks and expert consensus on optimal content coverage for each construct-guided decision. As a result of the expert feedback, the number of items in each sub-dimension remained at seven items in the Metacognitive Self-Regulation subscale, 4 in the Self-Efficacy subscale, and 5 in each of the remaining subscales. Consequently, the draft version of the Self-Regulation for AI-Based Learning Scale (SRAILS) consisted of 46 items. The item distribution across subscales is presented in Table 3.

Table 3. Items of the Self-Regulation for AI-Based Learning Scale (SRAILS)

Dimension	Sub-Dimension	Items
1. Motivational Components	1.1 Intrinsic Motivation	- I enjoy learning new things by using AI tools. - My curiosity increases during AI-supported learning. - Working with AI makes my learning process more interesting. - I feel more engaged during AI-supported learning. - Learning with AI increases my interest in course materials.
	1.2 Extrinsic Motivation	- Using AI tools help me improve my academic performance. - Learning with AI gains me appreciation from my teachers or peers. - Getting higher grades in AI-supported learning is important to me. - Working with AI gives me an advantage for my future career. - Learning with AI increases my competitiveness.
	1.3 Self-Efficacy	- I believe I can succeed in AI-based learning processes. - I can use AI tools effectively. - I can overcome the challenges I face during AI-supported learning. - I can study independently in AI-based learning environments.
2. Cognitive and Metacognitive Strategies	2.1 AI-Supported Cognitive Strategies	- I use AI tools to summarize lesson content and identify key points. - I organize information using AI-supported visuals, concept maps, or graphs. - I explore connections between topics with the help of AI tools. - I engage in interactive exercises using AI to better understand the content. - I access additional resources related to the topic using AI-based content suggestions.
	2.2 Metacognitive Self-Regulation	- I continuously evaluate my learning process while working with AI. - I set small goals for myself in AI-supported learning. - I reflect on which strategies work best for me when using AI. - I try to manage distractions during AI-supported learning. - I switch to alternative strategies when needed while learning with AI. - I assess AI-generated content and adapt my learning methods accordingly. - I compare AI-generated information with reliable sources to verify its accuracy.
3. Time and Study Management	3.1 AI-Supported Time Management	- I use my time efficiently during AI-supported learning. - I plan my study schedule using AI tools. - I stick to my planned time schedule during AI-supported learning. - I can better organize my study process with the help of AI tools. - I feel that I manage my time better while working with AI.
	3.2 Task Management	- I prioritize tasks during AI-supported learning. - I focus on completing the tasks I set while studying with AI. - I control my study process by effectively using AI tools. - I use different strategies to maintain focus during AI-supported learning. - I act in a planned manner to achieve my goals in AI-supported learning.
4. Environmental Self-Regulation	4.1 Resource Management for AI Use	- I carefully select the most appropriate resources when working with AI. - I evaluate which sources are reliable in AI-supported learning. - I compare various sources when using AI tools to acquire the best information. - I search for additional materials or online resources for AI-supported learning. - I have developed the habit of verifying information from AI with other sources.
	4.2 Technological Adaptation and Flexibility	- I am willing to learn and use new AI tools. - I can quickly adapt to technological changes in AI-supported learning. - I try alternative solutions when encountering technical problems with AI tools. - I explore and select suitable AI tools for my learning needs. - I am open to discovering different learning methods using AI technologies.

In the next phase, exploratory factor analysis (EFA) was conducted to examine the underlying factor structure of the scale. EFA was applied using data from 410 participants. Principal Axis Factoring (PAF) was chosen as the extraction method, which is one of the most widely used techniques in the social sciences due to its robustness in identifying latent structures (Fabrigar et al., 1999). The Promax oblique rotation method (kappa=4) was used to allow for correlated factors, which is appropriate for psychological constructs that are theoretically expected to be related.

Following the EFA, confirmatory factor analysis (CFA) was performed with data from a separate sample of 340 participants to test the factor structure identified in the EFA. CFA aims to verify the measurement model and assess its fit to the data. Model fit was evaluated using various indices, including $\chi 2/df$, standardized root mean residual (SRMR), root mean square error of approximation (RMSEA), comparative fit index (CFI), and Tucker-Lewis index (TLI), as recommended by Hu and Bentler (1999).

Additionally, convergent and discriminant validity were assessed by calculating composite reliability (CR), average variance extracted (AVE), maximum shared variance (MSV), and maximum reliability (MaxR(H)). To examine the scale's reliability, Cronbach's alpha and McDonald's omega coefficients were calculated for each subscale and the entire scale. A value of .70 or higher was considered acceptable for internal consistency (Nunnally & Bernstein, 1994). The scale was administered to 287 university students for criterion-related validity, and Pearson correlations were calculated between the nine dimensions and external variables, including GPA, technology interest, and digital literacy levels. These procedures ensured that the scale is psychometrically sound and suitable for measuring university students' self-regulation in AI-based learning contexts.

Results

Exploratory Factor Analysis Results

Exploratory factor analysis (EFA) was conducted separately for each dimension of the Self-Regulation for AI-Based Learning Scale (SRAILS) to examine the factorial structure and internal consistency of individual constructs. This approach was adopted for several theoretical and methodological reasons. First, given the multidimensional nature of self-regulated learning and technology adaptation, conducting separate analyses allows for a more precise examination of each dimension's internal structure without the potential confounding effects of cross-loadings from other dimensions. Second, this strategy identifies any problematic items within specific dimensions that might be masked in a comprehensive analysis. Third, separate EFAs provide clearer evidence for the unidimensionality of each construct, which is essential for establishing construct validity.

Before conducting each EFA, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was calculated to assess whether the data were suitable for factor analysis, with values above .60 considered adequate and above .80 indicating excellent suitability (Yurt, 2023). Additionally, Bartlett's test of sphericity was performed to examine whether the correlation matrix significantly differed from an identity matrix, thereby confirming the appropriateness of factor analysis. Principal axis factoring was employed as the extraction method, as it is particularly suitable for identifying underlying latent constructs. The results of the exploratory factor analyses for all nine dimensions are presented in Table 4.

Table 4. Exploratory Factor Analysis Results for SRAILS Dimensions

Factor	Item	Factor Loading	KMO Value	Bartlett's Sphericity Test	Eigenvalue	Variance Explained (%)
Intrinsic Motivation (IM)	IM1	.813	.834	χ^2=1132.095; df=10; p<.001	3.268	65.364
	IM2	.863				
	IM3	.813				
	IM4	.756				
	IM5	.795				
Extrinsic Motivation (EM)	EM1	.762	.850	χ^2=749.597; df=10; p<.001	2.802	56.045
	EM2	.736				
	EM3	.801				
	EM4	.639				
	EM5	.794				
Self-Efficacy (SE)	SE1	.851	.854	χ^2=921.708; df=6; p<.001	2.900	72.491
	SE2	.887				
	SE3	.821				
	SE4	.846				
Cognitive Strategies (CS)	CS1	.643	.822	χ^2=762.176; df=10; p<.001	2.746	54.913
	CS2	.731				
	CS3	.855				
	CS4	.783				
	CS5	.674				
Metacognitive Self-Regulation (MSR)	MSR1	.707	.887	χ^2=1315.918; df=21; p<.001	3.948	56.405
	MSR2	.814				
	MSR3	.721				
	MSR4	.809				
	MSR5	.770				
	MSR6	.765				
	MSR7	.658				
Time Management (TM)	TM1	.634	.836	χ^2=76.798; df=10; p<.001	2.761	55.215
	TM2	.622				
	TM3	.713				
	TM4	.889				
	TM5	.821				
Task Management (TSM)	TSM1	.763	.850	χ^2=789.690; df=10; p<.001	2.875	57.501
	TSM2	.834				
	TSM3	.799				
	TSM4	.713				
	TSM5	.671				
Resource Management for AI Use (RM)	RM1	.691	.834	χ^2=955.912; df=10; p<.001	3.413	6.843
	RM2	.711				
	RM3	.916				
	RM4	.790				
	RM5	.772				
Technological Adaptation and Flexibility (TAF)	TAF1	.718	.853	χ^2=806.403; df=10; p<.001	2.913	58.263
	TAF2	.770				
	TAF3	.758				
	TAF4	.814				
	TAF5	.753				

Table 4 presents the results of the exploratory factor analysis for the nine dimensions of the Self-Regulation for

AI-Based Learning Scale (SRAILS). The factor loadings for the items within each dimension range from .622 to .916. The KMO values for all subscales range between .822 and .887, and Bartlett's Test of Sphericity was statistically significant ($p < .001$), indicating the adequacy of the data for factor analysis. The variance explained by each factor ranges from 54.91% (Cognitive Strategies) to 72.49% (Self-Efficacy). These results suggest that each dimension effectively represents the intended construct and that the scale demonstrates strong construct validity.

Confirmatory Factor Analysis Results

Confirmatory factor analysis (CFA) was conducted to test the hypothesized nine-factor structure of the Self-Regulation for AI-Based Learning Scale (SRAILS), using data from 340 participants. Model fit was evaluated based on widely accepted indices (Kline, 2023). The results indicated an acceptable model fit: $\chi^2/df = 2.78$, SRMR = .05, RMSEA = .07, CFI = .92, and TLI = .91. These fit indices meet the recommended criteria suggested by Hu and Bentler (1999), supporting the adequacy of the nine-factor model in representing the data structure.
Accordingly, the findings suggest that the proposed nine-factor structure of the SRAILS demonstrates acceptable compatibility with the data. Factor loadings and the results of discriminant and convergent validity analyses for each factor are presented in Table 5.

Table 5. Confirmatory Factor Analysis Results and Reliability Statistics

Factor	Item	Factor loading	S.E.	C.R.	p	α	ω	CR	AVE	MSV
Intrinsic Motivation (IM)	IM1	.730	-	-	-	.902	.899	.891	.620	.746
	IM2	.784	.051	22.429	***					
	IM3	.846	.083	15.071	***					
	IM4	.779	.093	13.790	***					
	IM5	.794	.089	14.070	***					
Extrinsic Motivation (EM)	EM1	.768	-	-	-	.857	.858	.863	.558	.746
	EM2	.728	.083	13.777	***					
	EM3	.765	.070	14.585	***					
	EM4	.641	.089	11.934	***					
	EM5	.821	.074	15.849	***					
Self-Efficacy (SE)	SE1	.857	-	-	-	.913	.913	.913	.724	.583
	SE2	.893	.048	21.786	***					
	SE3	.821	.053	18.891	***					
	SE4	.830	.053	19.216	***					
Cognitive Strategies (CS)	CS1	.709	-	-	-	.856	.859	.860	.553	.670
	CS2	.711	.087	12.288	***					
	CS3	.831	.085	14.209	***					
	CS4	.798	.094	12.259	***					
	CS5	.656	.082	11.285	***					
Metacognitive Self-Regulation (MSR)	MSR1	.736	-	-	-	.899	.901	.900	.563	.670
	MSR2	.795	.080	14.551	***					
	MSR3	.716	.096	11.798	***					
	MSR4	.800	.082	14.672	***					
	MSR5	.748	.080	13.673	***					
	MSR6	.771	.081	14.124	***					

	MSR7	.679	.072	12.334	***					
Time Management (TM)	TM1	.695	-	-	-	.853	.858	.864	.562	.759
	TM2	.645	.116	9.900	***					
	TM3	.710	.102	12.166	***					
	TM4	.852	.096	14.368	***					
	TM5	.824	.104	13.941	***					
Task Management (TSM)	TSM1	.751	-	-	-	.868	.869	.871	.576	.759
	TSM2	.814	.062	15.312	***					
	TSM3	.806	.067	15.135	***					
	TSM4	.728	.068	13.520	***					
	TSM5	.690	.066	12.742	***					
Resource Management for AI Use (RM)	RM1	.755	-	-	-	.882	.887	.884	.606	.393
	RM2	.745	.068	13.717	***					
	RM3	.893	.075	16.424	***					
	RM4	.740	.078	13.569	***					
	RM5	.748	.089	12.473	***					
Technological Adaptation and Flexibility (TAF)	TAF1	.733	-	-	-	.874	.874	.875	.583	.571
	TAF2	.778	.072	13.987	***					
	TAF3	.765	.075	13.741	***					
	TAF4	.794	.074	14.281	***					
	TAF5	.746	.069	13.383	***					

CR = Composite Reliability; AVE = Average Variance Extracted; MSV = Maximum Shared Variance; $^{***}p < .001$

The confirmatory factor analysis results demonstrate satisfactory psychometric properties across all dimensions of the scale. All standardized factor loadings exceeded the minimum threshold of .60, ranging from .641 to .893, with most items displaying loadings above .70, indicating strong relationships between observed variables and their respective latent constructs (Table 5).

The critical ratio (CR) values for all freely estimated parameters were statistically significant ($p < .001$), confirming the significance of factor loadings. Composite reliability (CR), Cronbach α, and McDonald's ω values ranged from .853 to .913, all exceeding the recommended threshold of .70, demonstrating adequate internal consistency reliability for each factor. Average variance extracted (AVE) values varied between .553 and .724, with seven out of ten factors meeting the conventional criterion of .50, indicating that their respective latent constructs explain most variance in observed variables (Fornell & Larcker, 1981). The Self-Efficacy factor demonstrated the highest AVE (.724) and CR (.913), suggesting excellent convergent validity and reliability. Maximum shared variance (MSV) values were examined in relation to AVE to assess discriminant validity, with most factors showing MSV values lower than their corresponding AVE, supporting the distinctiveness of the constructs.

Descriptive Statistics and Factor Correlations for the SRAILS

Table 6 presents the means, standard deviations, and Pearson correlation coefficients among the nine factors of the Self-Regulation for AI-Based Learning Scale (SRAILS). All correlations were statistically significant at the $p < .01$ level (two-tailed), indicating strong interrelations among the factors. The strong inter-factor relationships support the internal consistency and construct validity of the scale, affirming its utility for assessing self-regulation in AI-based learning environments.

Table 6. Means, Standard Deviations, and Correlations Among Factors

Factors	M	SD	1	2	3	4	5	6	7	8	9
1. Intrinsic Motivation	18.17	4.25	-								
2. Extrinsic Motivation	18.58	4.20	.73**	-							
3. Self-Efficacy	14.59	3.51	.61**	.66**	-						
4. Cognitive Strategies	17.71	4.16	.66**	.64**	.58**	-					
5. Metacognitive Self-Regulation	24.33	5.95	.57**	.59**	.56**	.73**	-				
6. Time Management	16.84	4.23	.57**	.57**	.52**	.69**	.65**	-			
7. Task Management	17.47	4.27	.51**	.57**	.52**	.64**	.72**	.77**	-		
8. Resource Management	18.21	4.28	.35**	.33**	.42**	.48**	.55**	.48**	.56**	-	
9. Technological Adaptation and Flexibility	18.64	4.16	.60**	.63**	.67**	.63**	.60**	.60**	.58**	.54**	-

**p<0,01; N=340

Criterion-Related Validity Evidence

To assess the criterion-related validity of the Self-Regulation for AI-Based Learning Scale, the scale was administered to a total of 287 university students (54.6% male, n = 157; 45.4% female, n = 130). Pearson correlation coefficients were calculated between the nine dimensions of the scale and three external variables: academic grade point average (GPA), general interest in technology, and perceived digital literacy level. GPA, reported on a 4-point scale ranging from 0.00 to 4.00, served as an indicator of academic performance. Self-rated interest in technology and digital literacy, both measured on 5-point Likert-type items (1= Very low / none to 5= Very high / complete), were used as additional relevant external criteria. Descriptive statistics (mean and standard deviation) and correlation coefficients are presented in Table 7.

Table 7. Correlations Between the Self-Regulation for AI-Based Learning Scale Dimensions and External Criteria

Dimension of the Scale	GPA *(M = 2.72, SD = 0.79)*	Technology interest *(M = 3.59, SD = 0.93)*	Digital literacy *(M = 3.34, SD = 0.92)*
Intrinsic motivation *(M = 17.90, SD = 4.34)*	.46**	.42**	.35**
Extrinsic motivation *(M = 18.26, SD = 4.26)*	.45**	.38**	.36**
Self-efficacy *(M = 14.50, SD = 3.40)*	.60**	.46**	.49**
Cognitive strategies *(M = 17.46, SD = 4.19)*	.37**	.29**	.28**
Metacognitive self-regulation *(M = 23.97, SD = 5.79)*	.39**	.26**	.31**

Time management *(M = 16.72, SD = 4.18)*	.40**	.26**	.30**
Task management *(M = 17.22, SD = 4.35)*	.31**	.26**	.30**
Resource management *(M = 18.03, SD = 4.39)*	.27**	.20**	.32**
Technological adaptation and flexibility *(M = 18.32, SD = 4.19)*	.45**	.36**	.33**
SRAILS Total *(M = 162.38, SD = 30.88)*	.47**	.41**	.43**

N = 287, ** p < .01

Table 7 provides evidence supporting the criterion-related validity of the Self-Regulation for AI-Based Learning Scale. Positive and statistically significant correlations were found between the scale dimensions and external measures such as GPA, interest in technology, and perceived digital literacy. These findings indicate that higher self-regulation in AI-based learning contexts is associated with better academic performance and greater technological engagement.

Discussion

The primary aim of this study was to develop a theoretically grounded and psychometrically sound instrument to assess university students' self-regulation skills in artificial intelligence (AI)-supported learning environments. The resulting Self-Regulation for AI-Based Learning Scale (SRAILS) was designed to capture a comprehensive and multidimensional view of self-regulated learning through four main dimensions and nine sub-dimensions, including motivational components, cognitive and metacognitive strategies, time and task management, resource management, and technological adaptation. Data collected from 750 university students across various faculties in Türkiye demonstrated that the scale is valid and reliable for measuring self-regulation in AI-enhanced learning contexts. This section discusses each of the main findings in light of relevant literature and theoretical foundations. The first key finding was derived from the exploratory factor analysis (EFA), which supported each subdimension's internal coherence and conceptual distinction. Factor loadings ranged from .622 to .916, exceeding the commonly accepted threshold of .40 for social science research (Field, 2018). Kaiser-Meyer-Olkin (KMO) values ranged between .822 and .887, indicating excellent sampling adequacy (Yurt, 2023). The explained variance for each factor ranged from 54.9% (Cognitive Strategies) to 72.4% (Self-Efficacy), surpassing the commonly accepted 50% threshold (Fabrigar et al., 1999). These results confirm the proposed factor structure's theoretical foundation and empirical coherence, supporting the content validity of the SRAILS. This robust factorial structure aligns with Pintrich's (2000) conceptualization of self-regulated learning as a multidimensional construct, where distinct yet interrelated components such as motivation and cognition contribute to effective learning. The high variance explained by the Self-Efficacy subdimension (72.4%) underscores its critical role in AI-supported learning, resonating with Bandura's (1997) theory that self-efficacy beliefs drive students' engagement with complex technological tools, enhancing their ability to navigate AI environments effectively.

The second significant finding involved confirmatory factor analysis (CFA), which confirmed the nine-factor structure of the scale as a good fit for the data. The model fit indices ($\chi^2/df = 2.78$, SRMR = .05, RMSEA = .07, CFI = .92, TLI = .91) were all within acceptable ranges as defined by Hu and Bentler (1999), providing strong support for the structural validity of the scale. In addition, convergent and discriminant validity was established by analyzing average variance extracted (AVE) and maximum shared variance (MSV). AVE values ranged from .553 to .724, with most subdimensions exceeding the .50 threshold, indicating that most of the variance in each construct is captured by its indicators (Fornell & Larcker, 1981). MSV values were lower than the corresponding AVE scores for each factor, demonstrating discriminant validity and confirming that each construct is empirically distinct. These findings are consistent with the conceptual frameworks proposed by Pintrich (2000) and Zimmerman (2002), emphasizing the separable yet interrelated nature of motivational, cognitive, and contextual self-regulation components. The acceptable model fit supports the applicability of SRAILS in capturing the unique dynamics of AI-assisted learning, as highlighted by Lan and Zhou (2025), who note that effective self-regulation in AI contexts requires distinct skills tailored to technological interactions. The strong convergent validity, particularly for Self-Efficacy (AVE = .724), reflects findings by Wang et al. (2025), suggesting that students' confidence in using AI tools is pivotal for leveraging personalized feedback and adaptive content, thereby enhancing learning outcomes.

The fact that both alpha and omega values met the criteria further supports the scale's internal consistency across classical and modern reliability frameworks. These findings suggest that the items within each subdimension consistently reflect their respective constructs, reinforcing the scale's applicability for research and educational settings. This high reliability aligns with the need for robust measurement tools in AI-enhanced learning environments, as emphasized by Guan et al. (2025), who argue that reliable assessment of self-regulation is essential for designing interventions that support students' use of educational chatbots. The consistency across subscales, particularly in Metacognitive Self-Regulation ($\alpha = .899$, $\omega = .901$), corroborates Zimmerman's (2002) assertion that metacognitive processes are central to self-regulated learning, especially in technology-rich contexts where students must actively monitor and evaluate AI-generated content.

The third significant finding pertains to the correlations among the scale's subdimensions, which revealed substantial and statistically significant positive relationships ($p < .01$). Particularly high correlations were observed between Cognitive Strategies and Metacognitive Self-Regulation ($r = .73$), Time Management ($r = .69$), and Task Management ($r = .64$), indicating that these components function interactively Parte of a broader self-regulation system. This finding is consistent with Zimmerman's (2000) view of self-regulated learning as a dynamic and interdependent process. Furthermore, the strong correlation between Technological Adaptation and Self-Efficacy ($r = .67$) highlights how students' adaptability to new AI tools is closely linked to their confidence in using such technologies. This finding aligns with recent research emphasizing the role of AI literacy and student agency in navigating generative AI environments (Lan & Zhou, 2025; Guan et al., 2025). These robust interrelationships suggest that the scale measures independent facets of self-regulation and reflects the holistic nature of learning regulation in AI-supported environments. The strong correlations among dimensions, particularly between Cognitive Strategies and Metacognitive Self-Regulation, support findings by Nguyen et al. (2024), who observed that students using AI for summarizing and conceptual mapping exhibit enhanced metacognitive awareness, bolsters their learning efficiency. Similarly, the significant correlation between Technological Adaptation and Self-Efficacy aligns with Xiao et al. (2024), who found that students' confidence in AI tool usage is closely tied to their ability to adapt to new technological platforms, reinforcing the importance of digital literacy in AI-supported learning contexts.

Lastly, an important finding pertains to the criterion-related validity of the SRAILS, which was supported by statistically significant correlations between the scale dimensions and external measures, including academic GPA, technology interest, and digital literacy. All scale dimensions were positively associated with these external indicators (ranging from $r = .20$ to $r = .60$, $p < .01$), demonstrating the practical relevance of self-regulation in AI-based learning environments. In particular, Self-Efficacy showed the strongest correlation with GPA ($r = .60$), suggesting that students who feel more competent and autonomous in using AI tools also tend to perform better academically. This finding is consistent with Bandura's (1997) assertion that self-efficacy beliefs strongly predict academic achievement. Likewise, significant associations between Technological Adaptation and digital literacy and technology interest ($r = .33$ and $r = .36$, respectively) highlight the interconnectedness of students' digital competencies and their regulatory capacities in AI-supported learning contexts. These results provide robust evidence for the scale's criterion validity and reinforce the argument that self-regulated learning behaviors, especially in AI-enhanced environments, are meaningfully linked to students' academic outcomes and technological engagement (Wang et al., 2025; Xiao et al., 2024). Therefore, the SRAILS demonstrates sound psychometric properties and offers valuable insights into how students' self-regulation skills align with their academic success and technological readiness in AI-integrated learning settings.

Study Limitations and Future Research Directions

While the present study provides robust evidence for the validity and reliability of the Self-Regulation for AI-Based Learning Scale (SRAILS), several limitations must be acknowledged. First, data were collected exclusively from university students in Türkiye via an online survey. This situation limits the generalizability of the findings across diverse cultural or educational contexts. Future research should examine the scale's psychometric properties in different countries and learning settings, allowing for cross-cultural comparisons and potential adaptations. Moreover, future studies might consider how the scale could be adapted for different age groups or academic disciplines to enhance its broader applicability.

Second, the study relied solely on self-report data, which may be subject to social desirability bias or inaccuracies in students' self-assessments. In addition, online data collection methods may further exacerbate these issues by introducing attention-related limitations or increasing the likelihood of socially desirable responses. Future studies could adopt mixed-method designs that incorporate behavioral tracking, learning analytics, or observational data to gain deeper insights into students' actual use of AI tools and corresponding self-regulatory behaviors (Klar, 2025; Wu et al., 2025).

Third, the current research focused on individual-level self-regulation skills. However, AI-supported collaborative learning environments may involve shared regulation and co-regulation strategies that SRAILS does not capture.

Future studies could explore how self-regulation manifests in group-based AI-enhanced learning contexts and how collaborative AI usage influences regulatory development.

Finally, while comprehensive, the current 46-item structure of SRAILS may be time-consuming for practical use in classroom settings. Future studies could explore the development of a shorter version of the scale to facilitate quick administration in educational contexts, such as formative assessments during AI-integrated courses. Developing a parallel teacher-report version of SRAILS could provide complementary perspectives on students' self-regulation behaviors, enhancing the scale's applicability in diverse educational settings. Such adaptations would make the scale more versatile for research and practical applications.

Conclusion

As AI technologies increasingly integrate into educational environments, students' ability to self-regulate their learning in these contexts has become a critical competency. This study developed and validated the Self-Regulation for AI-Based Learning Scale (SRAILS) to address a pressing need for a context-specific tool to assess students' motivational, cognitive, behavioral, and environmental regulation skills in AI-supported learning.

The results demonstrated that SRAILS is a valid and reliable measure, with strong evidence from exploratory and confirmatory factor analyses, convergent and discriminant validity tests, and high internal consistency across all subscales. Moreover, the positive and meaningful correlations among the scale's dimensions highlight the interdependent nature of self-regulation in AI-enhanced environments.

SRAILS represents a significant contribution to the literature by bridging the gap between classical self-regulation theory and the emerging demands of digital-age learning. It provides researchers, educators, and instructional designers with a practical tool to assess learners' readiness for AI-enhanced education and to inform the development of personalized and effective teaching strategies. The scale's robust psychometric properties make it adaptable across diverse institutional contexts, such as community colleges, vocational schools, or online learning platforms like Learning Management Systems (LMSs), where AI tools are increasingly embedded. Additionally, translating SRAILS into multiple languages could facilitate its application in global educational settings, enabling cross-cultural self-regulation studies in AI-supported learning. These efforts would enhance its utility in fostering inclusive and equitable AI-driven education worldwide.

Moreover, criterion-related validity findings revealed significant correlations between the SRAILS dimensions and external indicators such as GPA, technology interest, and digital literacy, further supporting the scale's practical relevance. These results demonstrate that students with higher self-regulation skills show better academic outcomes and greater technological engagement. This outcome confirms that the scale captures essential competencies for success in AI-enhanced learning contexts.

Furthermore, SRAILS can serve as a diagnostic tool to identify students struggling with self-regulation in AI-based learning environments, enabling educators to design targeted interventions, such as workshops on effective

AI tool use or metacognitive strategy training, to support these learners (Guan et al., 2025; Wu et al., 2025). Such interventions could help mitigate issues like over-reliance on AI shortcuts or superficial engagement, fostering deeper learning and critical thinking skills. As the role of AI in education continues to grow, this scale offers a valuable foundation for future empirical studies and educational innovations that prioritize student agency, autonomy, and adaptive learning.

Author(s)' Statements on Ethics and Conflict of Interest

***Ethics Statement*:** We hereby declare that research/publication ethics and citing principles have been considered in all the stages of the study. We take full responsibility for the content of the paper in case of dispute. Ethical review board name: Bursa Uludağ University Social and Humanities Scientific Research Ethics Committee. Date of ethics review decision: 25 April 2025. Ethics assessment document issue number: 26.

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Appendix

The Self-Regulation for AI-Based Learning Scale Turkish Version

(Yapay Zekâ Destekli Öğrenmede Öz-Düzenleme Ölçeği Türkçe Versiyonu)

Boyut	Alt Boyut	Maddeler
1. Motivasyonel Bileşenler	1.1 İçsel Motivasyon	- AI araçlarını kullanarak yeni şeyler öğrenmek bana keyif verir. - AI destekli öğrenme sürecinde merakım artar. - AI ile çalışmak, öğrenme sürecimi daha ilginç hale getirir. - AI destekli öğrenme sürecinde kendimi daha aktif hissederim. - AI kullanarak öğrenmek, ders materyallerine olan ilgimi artırır.
	1.2 Dışsal Motivasyon	- AI araçlarını kullanmak, akademik başarımı artırmama yardımcı olur. - AI ile öğrenmek, öğretmenlerim veya arkadaşlarım tarafından takdir edilmemi sağlar. - AI destekli öğrenme sürecinde daha yüksek notlar almak benim için önemlidir. - AI ile çalışmak, gelecekteki kariyerim için bana avantaj sağlar. - AI kullanarak öğrenmek, rekabet gücümü artırır.
	1.3 Öz-Yeterlik	- AI tabanlı öğrenme sürecinde başarılı olabileceğime inanıyorum. - AI araçlarını etkili bir şekilde kullanabilirim. - AI destekli öğrenme sırasında karşılaştığım zorlukları aşabilirim. - AI tabanlı öğrenme süreçlerinde bağımsız olarak çalışabilirim.
2. Bilişsel ve Metabilişsel Stratejiler	2.1 Bilişsel Stratejiler	- AI araçlarını kullanarak ders içeriklerini özetleyip önemli noktaları belirlerim. - AI destekli görseller, kavram haritaları veya grafikler oluşturarak bilgileri örgütlerim. - AI araçlarını kullanarak öğrendiğim konular arasındaki bağlantıları keşfederim. - AI ile interaktif alıştırmalar yaparak bilgileri daha iyi anlamaya çalışırım. - AI tabanlı içerik önerilerini kullanarak konuyla ilgili ek kaynaklara ulaşırım.
	2.2 Metabilişsel Öz Düzenleme	- AI ile çalışırken öğrenme sürecimi sürekli olarak değerlendiririm. - AI destekli öğrenme sürecinde kendime küçük hedefler koyarım. - AI araçlarını kullanırken, hangi stratejinin benim için en iyi olduğunu düşünürüm. - AI destekli öğrenme sırasında dikkatimi dağıtan unsurları kontrol etmeye çalışırım. - AI kullanarak öğrenirken, gerektiğinde farklı stratejilere geçiş yapabilirim. - Yapay zeka içeriğini değerlendirip öğrenme yöntemlerimi buna göre uyarlarım. - AI ile üretilen bilgileri doğrulamak için güvenilir kaynaklarla karşılaştırırım.
3. Zaman ve Çalışma Yönetimi	3.1 Zaman Yönetimi	- AI destekli öğrenme süreçlerinde zamanı verimli kullanırım. - AI araçlarını kullanarak çalışma programımı planlarım. - AI destekli öğrenme sürecinde belirlediğim zaman çerçevesine sadık kalırım. - AI araçları sayesinde çalışma sürecimi daha iyi organize edebilirim. - AI ile çalışırken zamanımı daha iyi yönetebildiğimi hissediyorum.
	3.2 Görev Yönetimi	- AI destekli öğrenme sürecinde görevlerimi önem sırasına göre düzenlerim. - AI kullanarak ders çalışırken belirlediğim görevleri tamamlamaya odaklanırım. - AI araçlarını etkili bir şekilde kullanarak çalışma sürecimi kontrol altında tutarım. - AI destekli öğrenme sırasında dikkatimi korumak için farklı stratejiler kullanırım. - AI destekli öğrenme sürecinde belirlediğim hedeflere ulaşmak için planlı hareket ederim.
4. Çevresel Öz Düzenleme	4.1 Kaynak Yönetimi	- AI araçlarıyla çalışırken, en uygun kaynakları seçmeye özen gösteririm. - AI destekli öğrenme sürecinde hangi kaynakların güvenilir olduğunu değerlendirebilirim. - AI araçlarını kullanırken farklı kaynakları karşılaştırarak en iyi bilgiyi edinmeye çalışırım. - AI destekli öğrenme için ek materyaller veya çevrimiçi kaynaklar araştırırım. - AI araçlarının sunduğu bilgileri başka kaynaklarla doğrulama alışkanlığı edinirim.
	4.2 Teknolojik Uyum ve Esneklik	- Yeni AI araçlarını öğrenmeye ve kullanmaya istekliyim. - AI destekli öğrenme süreçlerinde teknolojik değişimlere hızlı uyum sağlayabilirim. - AI araçlarında karşılaştığım teknik sorunları çözmek için alternatif yollar denerim. - Öğrenme ihtiyaçlarım için uygun yapay zeka araçlarını keşfederek seçerim. - AI teknolojilerini kullanarak farklı öğrenme yöntemlerini keşfetmeye açığım.

1-Hiçbir zaman; 2-Nadiren; 3-Bazen; 4-Sık sık; 5-Her zaman