Development and Validation of the AI-Enhanced Self-Regulated Learning (AI-SRL) Scale

Desarrollo y validación de la escala de Aprendizaje Autorregulado con IA (AI-SRL)

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ABSTRACT

The integration of Artificial Intelligence (AI) into educational settings offers new opportunities for enhancing self-regulated learning (SRL) among students. However, current tools lack precision in measuring how AI influences learners' self-regulatory capabilities. This study introduces the AI-Enhanced Self-Regulated Learning (AI-SRL) Scale, designed to assess SRL in AI-supported educational environments. Through a rigorous scale development process involving a literature review, expert consultation, and systematic validation, we developed a comprehensive measurement instrument. The development employed a two-phase validation approach with separate samples for exploratory and confirmatory factor analyses. The final validated scale comprises 22 items organized into five dimensions: AI Competence, Learning Awareness, Learning Strategies, Engagement and Efficiency, and Ethical Collaboration. These factors capture the multifaceted nature of how students regulate their learning when using AI tools, from technical proficiency to ethical considerations. The scale demonstrated strong psychometric properties, with excellent internal consistency and robust construct validity. This validated instrument has practical applications for educators aiming to optimize AI integration in their classrooms, researchers investigating the intersection of AI and SRL, and institutions developing AI-enhanced curricula. The AI-SRL Scale provides a reliable framework for assessing how effectively students leverage AI tools while maintaining their self-regulatory capabilities, thereby contributing to more effective and responsible AI implementation.

Keywords: AI; AIED; self-regulated learning; AI-SRL; AI-SRL scale.

RESUMEN

La integración de la Inteligencia Artificial (IA) en entornos educativos ofrece nuevas oportunidades para mejorar el aprendizaje autorregulado (SRL) entre estudiantes. Sin embargo, las herramientas actuales carecen de precisión para medir cómo la IA influye en las capacidades autorregulatorias de los estudiantes. Este estudio presenta la Escala de Aprendizaje Autorregulado Mejorado por IA (AI-SRL), diseñada para evaluar el aprendizaje autorregulado en entornos educativos asistidos por IA. Mediante un riguroso proceso de desarrollo de escala que involucró revisión de literatura, consulta con expertos y validación sistemática, desarrollamos un instrumento de medición integral. El desarrollo empleó un enfoque de validación en dos fases con muestras separadas para análisis factoriales exploratorios y confirmatorios. La escala final validada comprende 22 ítems organizados en cinco dimensiones: Competencia en IA, Conciencia de Aprendizaje, Estrategias de Aprendizaje, Compromiso y Eficiencia, y Colaboración Ética. Estos factores capturan la naturaleza multifacética de cómo los estudiantes regulan su aprendizaje al usar herramientas de IA, desde competencia técnica hasta consideraciones éticas. La escala demostró sólidas propiedades psicométricas, con excelente consistencia interna y robusta validez de constructo. Este instrumento validado tiene aplicaciones prácticas para educadores que buscan optimizar la integración de IA en sus aulas, investigadores que investigan la intersección de IA y aprendizaje autorregulado, e instituciones desarrollando currículos mejorados con IA. La Escala AI-SRL proporciona un marco confiable para evaluar qué tan efectivamente los estudiantes aprovechan las herramientas de IA mientras mantienen sus capacidades autorregulatorias, contribuyendo así a una implementación de IA más efectiva y responsable.

Palabras clave: IA; AIED; aprendizaje autorregulado; AI-SRL; escala AI-SRL.

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INTRODUCTION

Self-regulated learning (SRL), a critical component of success in digital and lifelong learning, involves learners actively setting goals, monitoring progress, and adjusting behaviors to achieve academic success (Hilpert et al., 2023; Lai, 2024). In the digital age, SRL has become increasingly crucial for lifelong learning, enabling individuals to adapt to changing educational needs while promoting problem-solving abilities (Adams et al., 2024; Hilpert et al., 2023; Kong & Yang, 2024). As educational practices evolve, integrating advanced technologies like AI into learning environments offers opportunities to enhance SRL while addressing associated challenges.

The theoretical foundations of SRL are primarily based on two comprehensive frameworks that have shaped educational psychology for over three decades. Zimmerman's cyclical phase model, grounded in social cognitive theory, conceptualizes SRL as structured into three recursive phases: forethought, performance, and self-reflection (Panadero, 2017; Schunk & Zimmerman, 2012; Zimmerman, 1989). The forethought phase encompasses task analysis, including goal setting and strategic planning, alongside self-motivational beliefs such as self-efficacy, outcome expectations, and intrinsic interest. The performance phase involves self-control strategies such as focused attention, task strategies, and self-instruction, combined with self-observation through metacognitive monitoring of one's progress and strategy effectiveness. The self-reflection phase includes self-judgment, where learners evaluate their performance against standards, and self-reaction processes involving satisfaction responses and adaptive or defensive reactions that influence future learning efforts (Panadero, 2017; Tinajero et al., 2024).

Complementing this temporal view, Pintrich's (2000) framework offers a taxonomy with four phases —forethought/planning/activation, monitoring, control, and reaction/reflection—applied across four regulatory areas: cognition, motivation/affect, behavior, and context (Tinajero et al., 2024; Yot-Domínguez & Marcelo, 2017). This framework is particularly valuable for its explicit treatment of motivational regulation and contextual factors, offering a 16-cell matrix of specific regulatory processes that provides exhaustive coverage of SRL components. Pintrich's model emphasizes that SRL is an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior, guided and constrained by their goals and the contextual features in the environment (Panadero, 2017). These foundational models, while developed for conventional learning formats, provide the essential theoretical architecture for investigating how AI transforms established SRL processes.

The integration of AI in educational settings is transforming the structure of learning, bringing both opportunities and challenges in fostering SRL (Chang et al., 2023; Grüneke et al., 2024). AI technologies offer innovative ways to enhance traditional SRL strategies, providing personalized real-time feedback, flexible support, and real-time observing that supports learners in managing their learning processes effectively (Huang et al., 2023; Molenaar et al., 2023; Ng et al., 2024). Research demonstrates that AI applications efectively support metacognitive, cognitive, and behavioral regulation across Pintrich's four phases, with learning analytics dashboards significantly enhancing metacognitive awareness through real-time progress tracking and performance visualization (Gkintoni et al., 2025; Seo et al., 2021; Wang & Lin, 2023). Additionally, AI tools support metacognitive strategies through goal-setting support and strategic planning assistance, aligning with Zimmerman's forethought phase (Anggoro & Pratiwi, 2023; Liu et al., 2024). These systems can trace learning behaviors and provide insights into SRL processes, facilitating solutions that support the development of SRL (Chang et al., 2023; Jin et al., 2023; Molenaar et al., 2023).

Though AI tools have potential to support metacognitive skills and providing real-time monitoring (Dahri et al., 2024; Jin et al., 2023), researchers express concerns about overreliance on AI hindering essential skill development (Boguslawski et al., 2025). The literature highlights disagreement between AI's capacity to provide personalized support and the risk of diminishing learner autonomy through cognitive offloading effects, where frequent AI usage is negatively associated with critical thinking abilities (Chiu, 2024; Gerlich, 2025; Kong & Yang, 2024). Studies reveal that while learners perceive AI as useful for metacognitive, cognitive, and behavioral regulation, they show a strong preference for human support when addressing motivational needs, suggesting that AI applications consistently struggle to support motivational regulation—a critical component of Pintrich's framework (Lan & Zhou, 2025; Seo et al., 2021). Another critical aspect emphasized in studies is that studies emphasize the importance of maintaining a balance between AI support and human guidance in educational settings (Kong & Yang, 2024; Lai, 2024). While AI can provide detailed oversight and feedback mechanisms, educators play a crucial role in designing learning activities and providing emotional support (Chiu et al., 2023). Studies suggest that effective implementation of AI in SRL requires careful consideration of how these tools can complement rather than replace human interaction, particularly in supporting students' metacognitive development and motivation (Wang & Lin, 2023; Xia et al., 2023).

However, the potential of AI to fully enhance SRL has not yet been fully realized due to several barriers. While some studies highlight AI's potential to alleviate learning anxiety and enhance motivation (Biju et al., 2024), others raise concerns about the need for balanced integration to maintain active student participation (Grüneke et al., 2024). Furthermore, significant ethical concerns have arisen in multiple domains, including data privacy and surveillance issues, algorithmic bias that may embed educational inequalities, and academic integrity challenges as AI-generated content complicates the assessment of authentic learning (Gkintoni et al., 2025; Walter, 2024). To address these challenges, researchers emphasize the critical need for developing reliable measurement instruments to evaluate AI's impact on SRL processes (Baker, 2023; Grüneke et al., 2024; Jin et al., 2023; Molenaar et al., 2023).

Building on these theoretical foundations, the present study conceptualizes AI-enhanced SRL through five dimensions, extending and operationalizing Zimmerman's and Pintrich's frameworks for contemporary technological contexts. The AI Competence factor aligns with the forethought phase of both models, encompassing self-efficacy beliefs specifically related to AI tool usage and strategic planning for their deployment. Learning Awareness corresponds to metacognitive monitoring central to Pintrich's monitoring phase and Zimmerman's self-observation subprocess, capturing learners' awareness of their understanding and progress while interacting with AI. Learning Strategies and Engagement and Efficiency factors map onto the performance and control phases of both frameworks, reflecting cognitive strategy selection, adaptation, and the behavioral and motivational regulation necessary to persist in learning tasks. Critically, the Ethical Collaboration factor represents a necessary extension to classical models, operationalizing modern context regulation (Pintrich's fourth regulatory area) that addresses algorithmic bias, data privacy, and academic integrity concerns-regulatory demands unique to the AI era not anticipated in traditional SRL frameworks (Gkintoni et al., 2025; Walter, 2024).

The development of the AI-SRL Scale has important implications for evaluating diverse educational technology environments. In platforms utilizing real-time formative assessment tools like Socrative, the scale's Learning Awareness and Learning Strategies dimensions can measure whether instant feedback effectively prompts metacognitive monitoring and strategy adjustment (Bauer et al., 2025). Within Learning Management Systems such as Moodle featuring AI assistants like Corolair or CodeRunner Agent, the AI Competence and Engagement and Efficiency subscales can assess whether these 24/7 AI tutors enhance students' self-regulatory capabilities outside direct instructor supervision. For Intelligent Tutoring Systems providing adaptive scaffolding and personalized learning paths, the complete scale offers holistic evaluation of the entire regulatory cycle, from planning and strategy use to ethical considerations, offering valuable feedback for designing systems that are both intelligent and pedagogically sound (Wu & Chiu, 2025). As students increasingly engage with generative AI tools for academic work, the scale provides structured methods to investigate their regulation of inquiry, critical evaluation, and ethical AI use, addressing key gaps in understanding modern digital learning ecosystems (Li et al., 2025; Mohamed et al., 2025). Therefore, this study addresses the following research questions:

RQ1: How can AI-enhanced self-regulated learning be comprehensively measured through a scale that operationalizes and extends the established theoretical frameworks of Zimmerman and Pintrich for contemporary technological contexts?

RQ2: What is the factorial structure and psychometric properties of AI-SRL Scale when validated through exploratory and confirmatory factor analysis procedures?

RQ3: To what extent does the AI-SRL Scale function as a reliable and valid instrument for capturing the unique dimensions of SRL in AI-supported educational environments?

Literature Review

Recent advancements in AI have fundamentally transformed the landscape of SRL in educational settings, creating both unprecedented opportunities and complex challenges that demand careful theoretical and empirical examination. The literature reveals a nuanced picture where AI technologies demonstrate strong potential for supporting cognitive and metacognitive dimensions of SRL (Seo et al., 2021; Wang & Lin, 2023), while simultaneously presenting significant challenges for motivational regulation and raising critical ethical concerns about learner agency and digital well-being (Lan & Zhou, 2025).

The theoretical foundations of SRL, particularly Zimmerman's cyclical model and Pintrich's comprehensive framework, have proven remarkably robust when applied to AI-enhanced learning contexts. Zimmerman's three-phase cyclical structure—forethought, performance, and self-reflection—maps effectively onto AI applications (Chiu, 2024), with AI systems providing differential support across these phases. Research by Lan and Zhou (2025) found that while 50% of AI applications primarily support the performance phase, comprehensive support across all three phases remains rare (only 21% of applications), with the self-reflection phase receiving the least AI support. This suggests a continued need for human guidance in deeper reflective processes. Similarly, Pintrich's framework, with its four areas of regulation (cognitive, motivational/affective, behavioral, and contextual), finds clear parallels in AI-mediated learning environments (Yot-Domínguez & Marcelo, 2017), though motivational regulation remains particularly problematic (Jin et al., 2023; Seo et al., 2021).

AI technologies have demonstrated significant support for core SRL components across disciplines, particularly in cognitive and metacognitive domains. Recent empirical studies reveal significant relationships between AI self-efficacy and academic performance, with practical application of AI tools serving as the strongest predictor of self-efficacy (Bećirović et al., 2025). Research by Liang et al. (2023) found that student-AI interaction significantly improved learning achievement through enhanced cognitive engagement (β=0.046), while AI-powered feedback systems enhance students' metacognitive awareness through real-time progress tracking and performance visualization (Gkintoni et al., 2025; Molenaar et al., 2023). The implementation of AI in SRL reveals complex support-hindrance dynamics that require careful consideration. While AI tools like ChatGPT have enhanced students' research skills and supported self-directed learning through autonomy and engagement (Li et al., 2025), studies reveal concerning negative correlations ($r=-0.39$) between over-reliance on AI tools and critical thinking abilities, particularly among younger learners aged 17-25 (Gerlich, 2025). This "cognitive offloading" effect suggests that frequent AI usage may prevent the development of independent metacognitive skills, with learners becoming overly reliant on AI systems rather than developing autonomous self-regulation capabilities (Gerlich, 2025). Research by Glick et al. (2024) demonstrated that while AI-powered training modules significantly increased use of planning tools and goal-setting activities, the balance between AI support and learner agency remains a critical concern.

Perhaps the most significant finding across the literature is that AI applications consistently struggle to support motivational regulation, a critical component of effective SRL (Seo et al., 2021). Multiple systematic reviews confirm that while learners perceive AI as useful for metacognitive, cognitive, and behavioral regulation, they show a strong preference for human support when addressing motivational needs (Jin et al., 2023; Lan & Zhou, 2025). From a Self-Determination Theory perspective, while AI tools can support competence through personalized feedback and autonomy through learning pathway control (Chiu, 2024; Li et al., 2025), relatedness remains the weakest aspect of AI support.

Recent empirical evidence from 2020-2025 increasingly points toward hybrid human-AI regulatory systems as optimal approaches for supporting SRL. Research distinguishes between human-centered self-regulation, where AI serves as a facilitator providing tools and data for learner control, and AI-centered self-regulation, where AI generates SRL cycles based on data analysis (Lan & Zhou, 2025). The most effective implementations appear to involve human-AI interaction where AI engages with human-centered SRL cycles across behavioral, emotional, and cognitive dimensions while maintaining human agency (Wu & Chiu, 2025).

Overall, while AI presents transformative potential for SRL, the evidence suggests that effective implementation requires a carefully balanced approach that harnesses technological capabilities while preserving fundamental human elements of SRL. The development of new measurement tools like the AI-SRL Scale becomes crucial for providing deeper insights into the effectiveness and impact of AI tools, addressing the complex interplay between cognitive enhancement and potential motivational deficits, and guiding future integrations that maintain learner agency while leveraging AI's strengths in personalization and cognitive load management.

METHOD AND FINDINGS

In this study, we aimed to develop a scale to measure participants' SRL levels in the context of AI use. Despite established guidelines, researchers often face limitations in scale development, including sample characteristics, methodological issues, and psychometric challenges. To improve future practices, researchers should carefully consider these potential limitations and make informed methodological choices throughout the scale development process (Morgado et al., 2017). Therefore, acknowledging these limitations, we employed a robust methodology for the development of a reliable and valid scale in this study.

Participants

Two separate samples were used for the exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). The EFA sample consisted of 504 participants, while the CFA sample included 424 participants. Participants were recruited online through convenience and purposeful sampling (Creswell, 2014). Convenience sampling was used in a way that enabled us to reach participants more easily. We found participants from the universities that we somehow had connections with. Our sampling was purposeful, because we selected participants who could readily understand the scale items. Most of them were from the foreign language teaching or literature departments of universities. For those who were from other departments, we made sure they could easily understand the items on our scale. We preferred to collect data mainly from these departments to ensure clarity in item comprehension, which were in English. This might have affected the generalizability of the responses to some extent and may have influenced factor interpretation across some constructs. Future studies to validate the scale could collect data across diverse academic populations to enhance generalizability and statistics. The demographics of our participants are summarized in the table below.

Table 1
Demographics

Gender	N
Male	334
Female	594
Total	**928**

Age	N
18 or below	195
19	202
20	228
21	193
22	195
23 +	202
Total	**928**

Class	N
English prep class	212
Freshman/1st year	184
Sophomore/2nd year	260
Junior/3rd year	180
Senior/4th year+	92
Total	**928**

Department	N
English Language Teaching	288
English Language and Literature	262
Pharmacy	149
International Relations	31
Psychology	28
Law	25
Tourism and Guidance	23
Engineering	24
Others	98
Total	**928**

As Table 1 indicates, we had a total of 928 participants for the first and second steps (EFA and CFA) of the study. 594 participants (64.0%) were female, while 334 (36.0%) were male. Among departments, 288 participants (31.0%) were from English Language Teaching, 262 (28.2%) from English Language and Literature, and 149 (16.1%) from Pharmacy. Class distribution included 212 participants (22.8%) from preparatory English classes, 184 (19.8%) freshmen, 260 (28.0%) sophomores, 180 (19.4%) juniors, and 92 (9.9%) seniors. We collected some other information related to the participants' use of technology and AI in learning. Table 2 summarizes this information.

Table 2
Participants' Use of Technology and AI in Learning

Level of Using Technology in Learning	**N**
Very low	8
Low	46
Moderate	395
High	338
Very high	141
Total	**928**

Experience with AI	**N**
1 year	543
2 years	239
3 years	81
4 years	29
5 years	13
6 +	23
Total	**928**

Frequency of using AI for Learning	**N**
Every day	104
Several times a week	212
Once a week	141
Several times a month	180
Once a month	189
Not regularly/on need	102
Total	**928**

As seen from Table 2, the participants indicated their level of using technology in learning, with a vast majority reporting moderate (395, 42.5%), high (338, 36.4%) and very high levels (141, 14%). The ones whose level was low and very low were 5.8% of the participants. The participants also provided information on how much experience they had with AI. 543 of them (58.5%) had one year of experience, 239 had 2 years (25.7%), 81 had 3 years (8.7%), and the others had 4, 5, 6 or more years of experience with AI. Lastly, we gathered input from the participants on how often they used AI for learning. The number of participants who reported to be using it every day was 104 (11.2%), 212 (almost 22.8%) used it several times a week, 141 (15.2%) once a week, 180 (19.3%) several times a month, and 189 (20.3%) once a month. Also, 102 (almost 11%) participants reported using AI for learning when they needed it.

Item Generation

Scale development is a critical process in social and behavioral research, typically involving three main phases: item generation, scale construction, and scale evaluation (Boateng et al., 2018). The item generation phase begins with clearly defining the construct to be measured and creating an initial item pool (DeVellis, 1991). In this study, the initial pool of items was generated through a comprehensive review of the literature on SRL and AI. Content validity is assessed, often through expert review (Teeluckdharry et al., 2021). The items in our scale were designed to capture key dimensions of SRL in the context of AI, ensuring alignment with existing theoretical frameworks. The initial item pool underwent a rigorous content validation process by a panel of seven experts. These experts were selected based on specific criteria: (1) possession of a Ph.D. in Educational Technology, Educational Psychology, or a related field; (2) a minimum of five years of research experience; and (3) at least two peer-reviewed publications on either SRL or the application of AI in education. This purposive selection ensured substantial theoretical and practical expertise. The panel provided feedback on item clarity, relevance, and representativeness. Content validity was assessed using the Content Validity Index (CVI). Items achieving CVI ≥ .80 from at least 6 of 7 experts were retained. The Scale-level CVI average (S-CVI/Ave) was .92, exceeding the recommended threshold of .90. Items were revised or removed based on this feedback, yielding a preliminary scale for pilot testing. The literature suggests various sample sizes for pilot studies. Johanson and Brooks (2009) reported that Isaac and Michael (1995) and Hill (1998) suggested 10 to 30 samples for pilot studies, and they also stated that Mooney and Duval (1993) offered 30-50, and Hertzog (2008) suggested 25-40 for scale development. In our case, the pilot test was conducted with a sample of 33 participants representing similar characteristics of the target study groups. The pilot study aimed to identify any issues with item wording, response options, or overall scale length. Based on the pilot test results, minor revisions were made to enhance item clarity and reliability.

Exploratory Factor Analysis (EFA)

The scale construction phase includes pre-testing, survey administration, item reduction, and factor extraction (Boateng et al., 2018). After administering the scale to the first study group, we proceeded to the next step. The scale evaluation phase involves testing dimensionality, reliability, and validity (Teeluckdharry et al., 2021). The suitability of the data from the first sample ($N = 504$) for factor analysis was assessed. The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy was .96, indicating marvelous suitability for factor analysis (Kaiser & Rice, 1974). Additionally, Bartlett's Test of Sphericity was significant, $\chi^2 = 9846.80$, $p < .001$, confirming that the correlation matrix was not an identity matrix and was appropriate for factor analysis. Following this, Exploratory Factor Analysis (EFA) was carried out using SPSS 22 to examine and confirm the factor structure of the AI-SRL Scale. EFA was conducted to reveal the underlying factor structure and to identify clusters of related items, thereby establishing the construct validity of the scale by reducing the data into a smaller number of meaningful factors (Field, 2018). Principal Component Analysis (PCA) was employed as the extraction method, and promax rotation - one of the oblique rotation methods - was used to allow for correlations between factors (Kline, 2014; Muthén & Muthén, 2017). While Principal Axis Factoring (PAF) and Maximum Likelihood (ML) were tested, they did not yield stable or interpretable factor solutions. Given our aim of exploring the underlying dimensions and reducing the item pool into coherent components, PCA was selected for its robustness and interpretability in this context. This approach aligns with prior recommendations for early-stage scale development (Fabrigar & Wegener, 2012; Jolliffe, 2014). To further ensure validity, we used a separate dataset to conduct a Confirmatory Factor Analysis (CFA) via AMOS, which confirmed the PCA-derived factor structure with satisfactory model fit indices. The EFA most often yielded four factors, and in some cases five, based on eigenvalues larger than one. After trying a very large number of models with EFA and CFA, we chose the five-factor solution, because it yielded the best model fit. At the EFA stage, items with factor loadings of 0.4 or higher were retained, as this threshold was considered significant (Floyd & Widaman, 1995; Hair et al., 2010). During the EFA stage, three items were deleted due to cross-loadings below the 0.10 difference threshold (Büyüköztürk, 2018): *"I do not share my personal information when using*

AI tools," "I check the originality of AI-generated work before using it," and *"I ensure that my peers also use AI tools ethically."* At the CFA stage, nine additional items were removed due to low or marginal standardized loadings, redundancy with higher-loading items, or problematic cross-factor modification indices. These included items related to AI Competence (*e.g., "I can quickly learn to use new AI tools"*), reflective and evaluative Learning Awareness (*e.g., "I evaluate whether AI tools give me accurate information"*), and Ethical Collaboration (*e.g., "I discuss AI-related ethical issues with peers"*). Removal decisions were based on both statistical and conceptual considerations to ensure the final scale retained psychometric rigor and theoretical coherence. The items removed and the rationale for their exclusion are presented in Appendix B. The EFA revealed a five-factor structure, accounting for 62.42% of the total variance. Items loaded strongly on their respective factors, with factor loadings ranging from 0.44 to 0.96.

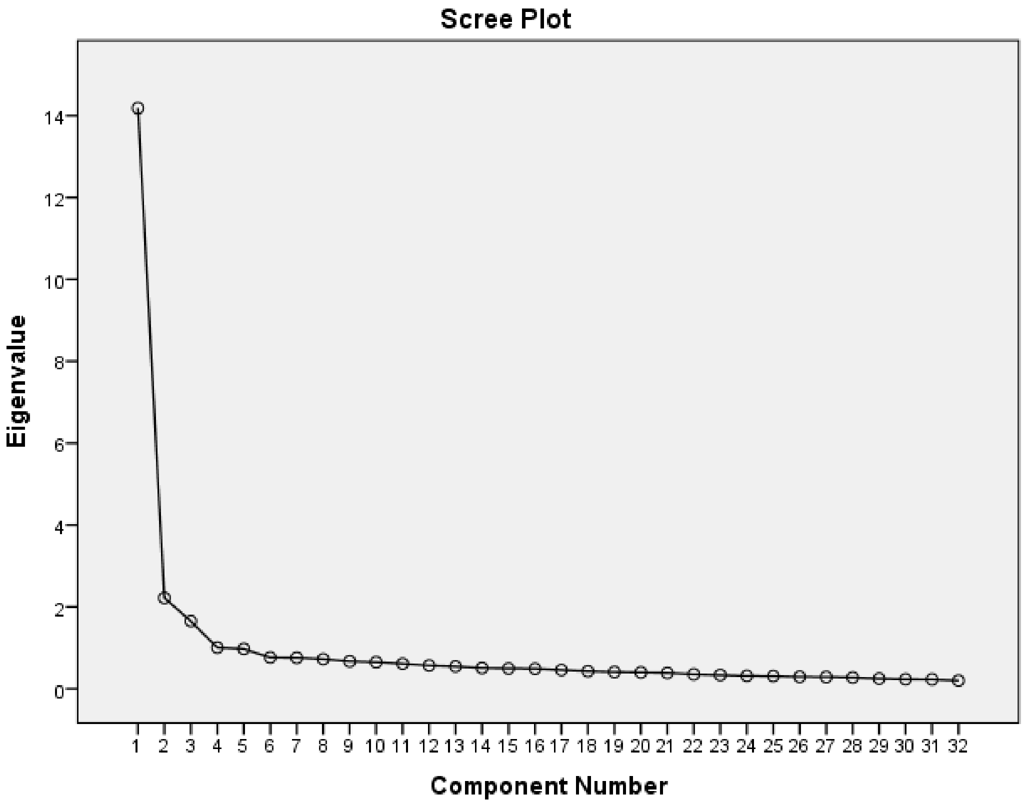
Table 3

Eigenvalues of Parallel Analysis

Factor	Initial eigenvalues	% of variance	Cumulative %
Factor 1	14.183	43.99	43.99
Factor 2	2.220	6.95	50.95
Factor 3	1.652	5.25	56.20
Factor 4	1.006	3.13	59.34
Factor 5	.996	3.080	62.42

As seen from Table 3, the eigenvalues for the first four factors are higher than one, and the fifth one is 0.99, just below 1.00. Because the fifth factor was supported by the previous literature and the upcoming analyses, we decided that it stay as a factor in the final scale. Parallel analysis was conducted using 1000 randomly generated data matrices with the same number of variables (31) and participants (504) as the actual dataset. The first three factors clearly exceeded the 95th percentile of random eigenvalues, strongly supporting their retention. Factors 4 and 5 had eigenvalues slightly below the 95th percentile threshold but were retained based on (a) theoretical alignment with established SRL frameworks, (b) adequate factor loadings (all >.40), and (c) improved model fit in subsequent CFA. This decision aligns with recommendations to consider multiple criteria beyond eigenvalues alone when determining factor retention (Fabrigar & Wegener, 2012). The five-factor solution was also supported by a scree plot, which illustrates the potential factors within the scale (Eisinga et al., 2013).

Figure 1
Scree Plot for the Initial Exploratory Factor Analysis



The scree plot also supported a five-factor solution, as the slope of the plot flattened considerably after the fifth factor. Appendix C presents the factor loadings for each item from the initial model, outlining the sub-dimensional nature of the scale. Following this analysis, items 21, 24, and 29 were removed. The remaining 31 items formed a five-factor structure, which was then subjected to CFA using data from the second study group. This subsequent analysis resulted in the final 22-item scale.

Confirmatory Factor Analysis (CFA)

After the initial EFA model was confirmed, we collected new data based on the latest EFA model. The new data was used for CFA. Sun (2005) indicates three main purposes for conducting a CFA: Construct validity evaluation, response pattern comparison and competing model comparison. We used it for evaluating construct validity and model comparison. The CFA, conducted with a separate sample (N = 424), was used to test the five-factor structure identified in the EFA. The initial model was refined based on standardized loadings and modification indices. Items with low loadings or those creating significant cross-factor covariance were iteratively removed to improve model fit while maintaining theoretical coherence. This process resulted in the final 22-item model. Table 2 summarizes the main fit indices from the CFA analyses.

Table 4
CFA Results

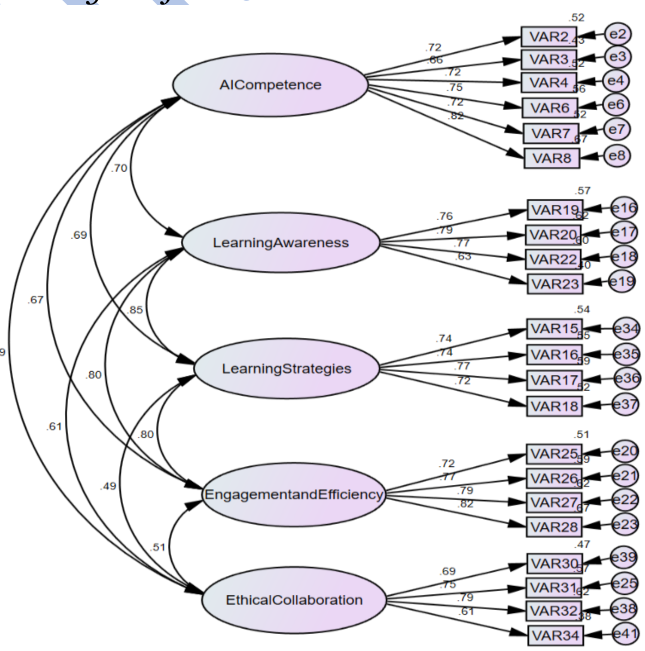
Key Indices	Hu and Bentler (1999)	Our Results
CFI	> .95 excellent, > .90 good > 80 sometimes acceptable	0.96
RMSEA	< .05 good, .10 moderate, > .10 not good	0.04
CMIN/DF	< 3 good, < 5 acceptable	2.82
GFI	> .95 excellent, >.90 good	0.94
AGFI	> .80	0.92
SRMR	< .09	0.04
TLI	> .95 excellent, >.90 acceptable	.95

As Table 4 indicates, the final model demonstrated a good fit to the data, as assessed against conventional fit criteria (Hu & Bentler, 1999). The fit indices were: χ^2/df (CMIN/DF) = 2.82, Comparative Fit Index (CFI) = .97, Tucker-Lewis Index (TLI) = .95, Root Mean Square Error of Approximation (RMSEA) = .04 (90% CI [.035, .045]), and Standardized Root Mean Square Residual (SRMR) = .04. As the CFI and TLI were above .95 and the RMSEA and SRMR were below .05, the five-factor model was confirmed as a valid representation of the data.

Confirmatory Factor Analysis (CFA) Model

The figure below illustrates the CFA model and the coefficients between variables and items.

Figure 2
Confirmatory Factor Analysis of AI-SRL Scale with Standardized Path Coefficients



The figure confirms the final model that consists of 5 factors and 22 items. The five factors confirmed through CFA represent distinct dimensions of AI-enhanced self-regulated learning with clear pedagogical implications. *AI Competence* (Factor 1, 6 items) captures learners' self-efficacy and technical proficiency in utilizing AI tools for educational purposes, reflecting their confidence in adapting to various AI interfaces, understanding AI-generated instructions, and effectively interpreting AI-produced information for learning. *Learning Awareness* (Factor 2, 4 items) encompasses metacognitive monitoring processes where learners consciously track their understanding, progress, and learning effectiveness while interacting with AI systems, including critical reflection on their dependency on these tools. *Learning Strategies* (Factor 3, 4 items) involves the selection, adaptation, and implementation of AI-supported cognitive strategies, including how learners use AI for finding effective study methods, improving problem-solving skills, and enhancing critical thinking through multiple perspective analysis. *Engagement and Efficiency* (Factor 4, 4 items) measures learners' behavioral and motivational regulation in maintaining participation, achieving permanent learning outcomes, and sustaining engagement when using AI tools adapted to their learning style. *Ethical Collaboration* (Factor 5, 4 items) represents a novel dimension addressing learners' awareness of responsible AI use, including considerations of personal responsibility, privacy concerns, potential biases, and information security in AI-assisted learning contexts. These factors collectively operationalize how contemporary learners navigate the complex landscape of AI-enhanced education while maintaining their self-regulatory capabilities. The complete validated 22-item AI-SRL Scale with all items organized by these five factors is provided in Appendix A. In the upcoming sections, it has been elaborated on the reliability and validity of the AI-SRL scale.

Reliability Analysis

We performed several tests to ensure the AI-SRL scale is a reliable scale. These tests are explained below.

Internal Consistency

Cronbach's alpha was calculated to assess the internal consistency of the overall scale and each factor, which is used to indicate the overall degree of homogeneity of test items. Cronbach's alpha values above .90 are considered to reflect excellent consistency, while values between .80 and .90 suggest good consistency. Values between .70 and .80 indicate acceptable internal consistency, values between .60 - .70 are questionable, .50 to .60 are poor, and values between .50 are unacceptable (George & Mallery, 2003). The overall scale demonstrated excellent internal consistency (α = .94, 95% CI [.93, .95]). The individual sub-factors also showed good to excellent reliability: AI Competence (α = .91), Learning Awareness (α = .88), Learning Strategies (α = .84), Engagement and Efficiency (α = .86), and Ethical Collaboration (α = .87). Detailed statistics, including item-factor correlations, are presented in Appendix D.

Split-half Reliability

Split-half reliability analysis was performed on the AI-SRL scale to further assess the consistency of the test items. Table 5 shows the results of this analysis.

Table 5
Split-half Reliability Analysis Results

	Number of Items	Max – Min Means	Means	Cronbach's Alpha	Correlation between Forms	Guttman Split-Half Coefficient	Spearman-Brown Coefficient
Part 1	11[a]	3.56 ± 3.16	3.39	0.90	0.80	0.89	0.89
Part 2	11[b]	3.59 ± 3.19	3.41	0.89			
Total	**22**	**3.59 ± 3.16**	**3.40**	**0.94**			

[a] The items are: 1, 3, 5, 7, 9, 11, 13, 15, 17, 19, 21.
[b] The items are: 2, 4, 6, 8, 10, 12, 14, 16, 18, 20, 22.

As Table 5 indicates, the Spearman-Brown coefficient was .89 (95% CI [.87, .91]), and the Guttman Split-Half coefficient was .89 (95% CI [.87, .91]), indicating excellent split-half reliability. The correlation between forms was .80 (95% CI [.77, .83]).

Validity

According to Cheung et al. (2024), convergent validity requires CR ≥ 0.70, standardized loadings ≥ 0.50, and AVE ≥ 0.50-all of which are met in our model. Table 6 shows the scores of AI-SRL scales.

Table 6
CR, AVE, MSV, and Factor Correlations

	CR	AVE	MSV	Ethical Collab.	AI Comp.	Learning Aware.	Engag. and Effic.	Learning Strategies
Ethical Collaboration	0.80	0.51	0.37	**0.71**				
AI Competence	0.87	0.54	0.49	0.59	**0.73**			
Learning Awareness	0.83	0.55	0.73	0.61	0.70	**0.74**		
Engagement and Efficiency	0.85	0.59	0.65	0.51	0.67	0.80	**0.77**	
Learning Strategies	0.83	0.55	0.73	0.49	0.68	0.85	0.80	**0.74**

Note: 95% confidence intervals for correlations are available in supplementary materials. All correlations significant at $p < .001$. CR = Composite Reliability; AVE = Average Variance Extracted; MSV = Maximum Shared Variance.

Discriminant validity was tested using multiple criteria: (a) no item cross-loads across constructs, (b) AVE for each construct exceeded squared inter-construct correlations, and (c) inter-factor correlations fell below the recommended values -none exceeded 0.85- (Cheung et al., 2024; Hair et al., 2010). While some high correlations were found among Learning Awareness, Engagement and Efficiency, and Learning Strategies, these constructs maintained theoretical distinctiveness within the AI-SRL framework. Thus, their retention was considered both psychometrically justifiable and conceptually meaningful.

Statistical analyses were performed using IBM SPSS Statistics 22 and AMOS 22. All confidence intervals were calculated at the 95% level using bias-corrected accelerated (BCa) bootstrap with 5000 resamples. Parallel analysis employed O'Connor's (2000) SPSS syntax, generating 1000 random correlation matrices for eigenvalue comparison. Significance levels were set at $\alpha = .05$ for all tests, with Bonferroni corrections applied for multiple comparisons where appropriate. The validated scale offers a reliable and valid measure of SRL in the context of AI, with potential applications in educational research and practice. Future research could explore the scale's use in diverse populations and settings.

DISCUSSION

This study successfully developed and validated the AI-SRL Scale, providing the psychometrically robust instrument specifically designed to measure SRL capabilities in AI-supported educational environments. For the preliminary analyses, a tool of 34 items was developed based on the literature and expert views. Factor analysis utilizing KMO revealed an excellent suitability (.96), and Bartlett's Test of Sphericity proved the multivariate normal distribution of the dataset. After EFA and PCA to establish meaningful factors and reveal correlations among these factors, 12 items were removed from the scale to preserve the scale's theoretical coherence and psychometric integrity. Based on the responses from 928 participants, EFA and CFA analyses were performed. The content validity, construct validity, internal consistency and split-half reliability results of the study proved that AI-SRL is a psychometrically sound scale in assessing the SRL in AI in educational environments. The finalized version of this scale involved 22 items under 5 factors, which are AI Competence, Learning Awareness, Learning Strategies, Engagement and Efficiency, and Ethical Collaboration.

This five-factor structure shows that AI use in educational environments deepens and contributes to the traditional construct of self-regulation by elaborating on competence, learning awareness, learning strategies, engagement and efficiency, and ethical collaboration. This new five-factor structure complies with the recent literature by highlighting how AI integration into educational settings advances the conventional SRL theories proposed by Zimmerman (1989) and Pintrich (1999). Furthermore, the AI Competence factor in the current study contributes to the previous literature. For example, Bećirović et al. (2025) explored a significant correlation between academic performance and AI self-efficacy. Also, AI Competence factor can be associated to cognitive regulation strategies of Pintrich (1999) since the current study highlighted that AI tools can assist elaboration strategies by providing individualized explanations and suggestions. Moreover, the Learning Awareness factor echoes Zimmerman's self-observation process of performance phase (Panadero, 2017; Zimmerman, 1989) by indicating AI's potentials in enhancing metacognitive monitoring and learning awareness. Gkintoni et al. (2025) revealed that feedback from AI tools, enabling simultaneous performance measuring, promote learners' metacognitive awareness. This awareness supports students in following their learning processes more consciously. In addition, the factor of Ethical Collaboration contributes to the previous literature. For example, the issues such as data privacy, surveillance, algorithmic bias, and academic integrity were highlighted as ethical concerns that may directly affect SRL in educational contexts in terms of AI applications (Gkintoni et al., 2025; Walter, 2024). Thus, this factor underpins students' ethical responsibilities in using AI tools and highlights the challenges that may emerge in AI-based educational environments. The Ethical Collaboration factor represents a paradigmatic extension beyond classical SRL frameworks, introducing dimensions that neither Zimmerman nor Pintrich anticipated. This factor operationalizes what Pintrich (1999) termed "context regulation" but extends it to encompass algorithmic transparency, data sovereignty, and collaborative ethics in human-AI interactions. The emergence of this factor as statistically and conceptually distinct suggests that ethical considerations in AI-mediated learning constitute not merely an add-on to existing frameworks but a fundamental regulatory domain requiring dedicated theoretical attention. This finding aligns with recent calls for "algorithmic literacy" as a core competency in digital education (Walter, 2024), suggesting that self-regulated learners must now navigate not only cognitive and motivational challenges but also ethical complexities inherent in AI-assisted learning ecosystems. Regarding the factor of Engagement and Efficiency, AI technologies can present invaluable potentials to support cognitive and metacognitive dimensions of SRL while they may fall short in motivational regulation (Lan & Zhou, 2025; Seo et al., 2021; Wang & Lin, 2023). Considering Zimmerman's (1989) and Pintrich (1999) theories, motivational regulation is closely associated with trust, affinity, and individualized affective support which are provided by AI supported educational tools. Thus, Engagement and Efficiency as a factor in the current study emerges as a critical area for new research to elaborately investigate the motivational impacts of AI implementations. The Learning Strategies factor aligns with both Pintrich's (1999) cognitive control phase and Zimmerman's (1989) performance phase, capturing how learners select, adapt, and implement AI-supported cognitive strategies for learning. This factor reflects the literature's findings that AI tools effectively support strategy adaptation and selection, with students using AI to find effective study methods, improve problem-solving skills, and enhance critical thinking through multiple perspective analysis (Liu et al., 2024; Seo et al., 2021). The inclusion of this factor acknowledges that contemporary learners actively integrate AI recommendations into their strategic repertoire, representing a shift from traditional strategy use to AI-augmented strategic learning approaches that require both technological fluency and metacognitive judgment about when and how to deploy AI-suggested strategies.

CONCLUSION AND FUTURE DIRECTIONS

Rapid advancements in AI tools have made it necessary for educational environments to adapt them into educational processes appropriately. Along with other psychological constructs, it has become evident that developing a measurement tool regarding SRL in using AI in educational environments to employ in research studies for various purposes seems essential. For this purpose, the current study aimed to conduct the validity and reliability study of AI-SRL scale to address this need in the literature. The current study proposed the AI-SRL scale, and it can be used as a psychometrically sound scale to measure students' SRL skills in AI use in educational environments. The AI-SRL scale can make an original contribution to the literature, and it has potential as an effective instrument for implementations in AI-mediated educational contexts. For future research, cross-cultural validation studies of this instrument can be conducted to analyze its applicability in different cultural settings. Also, the data of the current study were collected in higher education contexts, and the future data can be collected in secondary education contexts or professional contexts to see whether it yields different results.

The AI-SRL scale represents a pioneering contribution to educational measurement by being among the first validated instruments specifically designed to capture the multidimensional nature of SRL in AI-enhanced environments. Unlike generic SRL measures or technology acceptance scales, this instrument uniquely bridges theoretical foundations from educational psychology with contemporary realities of AI integration, offering researchers and practitioners a psychometrically robust tool for understanding how learners navigate the complexities of AI-mediated education. The scale's potential extends beyond individual assessment to inform institutional policy and pedagogical innovation. Educational institutions implementing AI-powered learning systems can utilize the scale to benchmark student readiness, identify support needs, and evaluate the effectiveness of AI integration initiatives. The five-factor structure provides actionable insights for curriculum designers, suggesting that AI literacy programs should address not only technical competence but also metacognitive awareness, strategic adaptation, motivational engagement, and ethical reasoning.

For future research, cross-cultural validation studies of this instrument can be conducted to analyze its applicability in different cultural settings. Also, the data of the current study were collected in higher education contexts, and the future data can be collected in secondary education contexts or professional contexts to see whether it yields different results. Future validation studies should prioritize cross-cultural investigations, particularly in non-Western educational contexts where collectivist learning orientations might interact differently with AI tools. The scale's applicability in K-12 settings warrants investigation, as younger learners may exhibit distinct patterns of AI-enhanced self-regulation. Professional training contexts, including corporate learning environments and continuing education programs, represent another frontier where the AI-SRL scale could illuminate how working professionals integrate AI tools into their lifelong learning practices. Longitudinal studies tracking changes in AI-SRL profiles over time would provide valuable insights into developmental trajectories and the impact of educational interventions.

PRACTICAL IMPLICATIONS AND LIMITATIONS

The AI-SRL scale can be implemented as an effective reliable tool from planning to assessment in educational settings. It can be applied to measure students' AI-SRL levels, learning analytics can be designed or observed based on the reports from the scale, and it can provide insights for instructional designs. Also, the scale can be employed in face to face, online, and hybrid education. The AI-SRL scale offers concrete applications for enhancing teaching practices across diverse educational modalities. In diagnostic assessment, educators can administer the scale at course onset to identify students who may struggle with AI-enhanced learning components, enabling targeted support interventions. For learning analytics applications, scale scores can be integrated with digital trace data to create comprehensive learner profiles, revealing patterns between self-reported AI-SRL capabilities and actual tool usage behaviors. This integration becomes particularly valuable in massive open online courses (MOOCs) where personalized support at scale remains challenging. In instructional design, the five-factor structure guides the development of scaffolding strategies tailored to different aspects of AI-enhanced learning. For instance, students scoring low on AI Competence might benefit from technical orientation modules, while those with weak Ethical Collaboration scores could engage with case studies on responsible AI use. In hybrid learning environments, the scale can inform decisions about when to deploy AI support versus human instruction, optimizing the blend based on students' self-regulatory profiles. Distance education programs can use the scale to assess whether students possess the requisite AI-SRL skills for success in autonomous learning environments, potentially incorporating scale-based prerequisites or preparatory courses.

However, the current study involved several limitations. First, most of the participants were chosen from foreign language teaching and English language literature departments of universities in Turkey. Involving most of the participants from two departments may limit generalizability of the findings to other higher education contexts. Second, convenience and purposeful sampling methods were used to reach the participants in this study. Non-random sampling may hinder the generalizability of the findings to other populations. Third, the items of the scale can be interpreted differently by individuals from different linguistic backgrounds. Last, disciplinary biases may influence the effective implementation of the instrument negatively. However, several limitations warrant consideration. The scale's development within Turkish higher education contexts, with participants predominantly from language-related disciplines, may have limited cross-cultural and cross-disciplinary generalizability. The English-language items may have introduced response biases among non-native speakers, potentially affecting measurement invariance across linguistic groups. Additionally, the rapidly evolving nature of AI technologies means the scale will require periodic updates to maintain relevance.

Ethical Approval

This research received ethical approval from Social Sciences University of Ankara, as per decision number 98038.

Ethical Use of AI Tools

In accordance with transparency principles, we disclose the use of AI tools in manuscript preparation. We utilized Claude Opus primarily for linguistic refinement—specifically to improve grammatical structures, enhance sentence flow, and ensure consistency in academic terminology across sections. This tool served exclusively as editorial assistants for language polishing, not for generating research content, data analysis, or theoretical contributions. All substantive content, including research design, data collection, statistical analyses, and interpretation of findings, represents original work by the authors. We maintained full editorial control throughout the writing process, critically reviewing and modifying all AI-suggested revisions. The authors assume complete responsibility for the accuracy, originality, and scholarly integrity of the final manuscript.

Data Availability

The data and materials used in this study are available upon request from the corresponding author.

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APPENDICES

Appendix A: Items from the AI-Enhanced Self-Regulated Learning (AI-SRL) Scale

Factors and Items	**Completely Disagree**				**Completely Agree**
AI Competence	**1**	**2**	**3**	**4**	**5**
1. I can easily use AI tools with different interfaces.	○	○	○	○	○
2. Active use of AI tools improves my ability to learn.	○	○	○	○	○
3. I can efficiently utilize AI tools to find information relevant to my studies.	○	○	○	○	○
4. I feel confident in my ability to learn via new AI tools.	○	○	○	○	○
5. The instructions from AI tools are easy to understand.	○	○	○	○	○
6. I can easily make sense of AI-generated information in my learning process.	○	○	○	○	○
Learning Awareness	**1**	**2**	**3**	**4**	**5**
7. Feedback from AI tools helps me understand my learning strengths.	○	○	○	○	○
8. AI-provided feedback helps me identify areas for improvement.	○	○	○	○	○
9. I assess the effectiveness of AI tools in helping me achieve my learning objectives.	○	○	○	○	○
10. I think critically about my dependency on AI tools for learning.	○	○	○	○	○
Learning Strategies	**1**	**2**	**3**	**4**	**5**
11. I adapt my study methods according to recommendations provided by AI tools.	○	○	○	○	○
12. I use AI tools to find the most effective ways to learn new subjects.	○	○	○	○	○
13. I utilize AI-generated information to improve my problem-solving skills.	○	○	○	○	○
14. By using AI tools to analyze different perspectives, I can enhance my critical thinking skills.	○	○	○	○	○
Engagement and Efficiency	**1**	**2**	**3**	**4**	**5**

Factors and Items	**Completely Disagree**				**Completely Agree**
AI Competence	**1**	**2**	**3**	**4**	**5**
15. My participation in learning activities is higher with AI use.	○	○	○	○	○
16. AI tools help me learn more permanently.	○	○	○	○	○
17. I think I learn better when I use AI tools.	○	○	○	○	○
18. I think AI tools that adapt to my learning style enhance my engagement in learning.	○	○	○	○	○
Ethical Collaboration	**1**	**2**	**3**	**4**	**5**
19. I know I have to take all the responsibility when I use AI tools for learning.	○	○	○	○	○
20. I am conscious of privacy concerns in AI-tools.	○	○	○	○	○
21. I am aware of potential biases in AI tools.	○	○	○	○	○
22. I am conscious about the security of the information that I provide to AI tools.	○	○	○	○	○

Appendix B: Items Removed from Final Model with Empirical and Conceptual Rationale

Stage	**Item (Full Wording)**	**Original Factor**	**Loading**	**Reason for Removal**
EFA	I use AI tools to check how effectively I'm learning.	Probably Learning Awareness	.463/.439	Cross-loading <0.10 difference; with loadings .463 and .439 for two factors
EFA	Thinking deeply about the reasons for using AI tools helps me apply them better in my studies.	Probably Learning Strategies	.285/.463	Cross-loading on two items; similar to other academic integrity items, also decreased the AVE when tried in CFA
EFA	I know how to use AI generated information ethically when learning with AI.	Probably Ethical Collaboration	.329/.-260/.491	Cross-loading <0.10 difference; with loadings .329, .-260 and .491 for three factors
CFA	I find it easy to adapt to the changing features in AI tools.	AI Competence	.66	Decreased the AVE; concept covered by stronger AI Competence items

CFA	I am skilled at using specific functions of AI tools (like data analysis or content recommendation) for learning.	AI Competence	.64	Decreased discriminant validity; probably vague
CFA	AI tools help me prioritize my learning goals.	Learning Awareness	.64	Low loading, decreased AVE and discriminant validity
CFA	AI tools help me access a wide range of learning resources.	Learning Awareness	.62	Decreased AVE; probably vague
CFA	AI tools make me more autonomous (independent) in my learning process.	Learning Awareness	.59	Low loading; weak representation of construct
CFA	AI tools help me manage my learning time better.	Learning Awareness	.63	Low loading; decreased AVE
CFA	AI tools help me develop strategies for learning tasks.	Learning Awareness	.65	Low loading; concept covered by other self-monitoring items
CFA	AI tools help me understand complex topics more easily.	Learning Awareness	.64	Decreased discriminant validity; better represented by other learning-monitoring items
CFA	I am skeptical about the capability of AI tools in providing information accuracy.	Ethical Collaboration	.65	Marginal loading; probably vague

Appendix C: Factor Loadings for the Initial EFA Model

	Factor1	Factor2	Factor 3	Factor 4	Factor 5
Item1	.860				
Item2	.853				
Item3	.555				
Item4	.698				
Item5	.693				
Item6	.690				
Item7	.672	.			
Item8	.628				
Item9		.665			
Item10		.464			
Item11		.676			
Item12		.776			

Item13	.489			
Item14	.449			
Item15			.725	
Item16			.751	
Item17			.835	
Item18			.589	
Item19	.684			
Item20	.571			
Item22	.498			
Item23	.669			
Item25				.636
Item26				.916
Item27				.861
Item28				.669
Item30		.625		
Item31		.867		
Item32		.789		
Item33		.729		
Item34		.850		

Note: All loadings significant at $p < .001$. Standard errors ranged from .028 to .045.

Appendix D: Cronbach's Alpha for Each Factor and Item-Factor Correlations

Factors/Item description	Corrected Item-total correlation	Cronbach's alpha if item deleted	Cronbach's alpha
Factor 1. AI Competence			
1. I can easily use AI tools with different interfaces.	.60	.94	
2. Active use of AI tools improves my ability to learn.	.60	.94	
3. I can efficiently utilize AI tools to find information relevant to my studies.	.66	.93	.88
4. I feel confident in my ability to learn via new AI tools.	.66	.93	
5. The instructions from AI tools are easy to understand.	.64	.93	
6. I can easily make sense of AI-generated information in my learning process.	.72	.93	
Factor 2. Learning Awareness			
7. Feedback from AI tools helps me understand my learning strengths.	.61	.94	
8. AI-provided feedback helps me identify areas for improvement.	.62	.93	
9. I assess the effectiveness of AI tools in helping me achieve my learning objectives.	.65	.93	.83
10. I think critically about my dependency on AI tools for learning.	.67	.93	

Factors/Item description	Corrected Item-total correlation	Cronbach's alpha if item deleted	Cronbach's alpha
Factor 3. Learning Strategies			
11. I adapt my study methods according to recommendations provided by AI tools.	.66	.93	.84
12. I use AI tools to find the most effective ways to learn new subjects.	.71	.93	
13. I utilize AI-generated information to improve my problem-solving skills.	.70	.93	
14. By using AI tools to analyze different perspectives, I can enhance my critical thinking skills.	.56	.94	
Factor 4. Engagement and Efficiency			
15. My participation in learning activities is higher with AI use.	.64	.93	.86
16. AI tools help me learn more permanently.	.60	.94	
17. I think I learn better when I use AI tools.	.63	.93	
18. I think AI tools that adapt to my learning style enhance my engagement in learning.	.74	.93	
Factor 5. Ethical Collaboration			
19. I know I have to take all the responsibility when I use AI tools for learning.	.58	.94	.84
20. I am conscious of privacy concerns in AI-tools.	.54	.94	
21. I am aware of potential biases in AI tools.	.60	.94	
22. I am conscious about the security of the information that I provide to AI tools.	.55	.94	
Whole scale			**.94**

Note: 95% CIs calculated using 5000 bootstrap samples. All item-total correlations significant at $p < .001$.

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