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Developing self-regulated artificial intelligence learning (SRAIL) Student Attitudes Scale☆

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ABSTRACT

This research aims to develop a valid and reliable scale for measuring students' attitudes towards integrating artificial intelligence (AI) in self-regulated learning (SRL). In this study, 250 children from the Ankara province in Turkey participated. Exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were used to analyse the data. The findings indicate that the scale consists of 17 items and two dimensions. The 17-item scale comprised two dimensions: Academic success (9 items, performance with AI, etc.) and study style (8 items, time management, etc.). Furthermore, the study determined the composite reliability index (CRI) as.86, thus indicating that the scale was highly valid and reliable. It is recommended that it be implemented among children from diverse countries and across various age groups.

1. Introduction

Technology-enhanced SRL represents an approach to education that employs digital tools to enhance the interactivity, personalisation and efficiency of learning processes (Sui et al., 2024). In this model, students engage actively with technology in the context of SRL processes, including goal setting, time management, strategy selection and progress monitoring (Radović & Seidel, 2025). Learning management systems, adaptive learning software and mobile applications facilitate more effective individual learning pathways by providing students with content tailored to their learning pace and needs (Lagos-Castillo et al., 2025). Furthermore, digital tools provide continuous feedback to children, enabling them to monitor their learning process and make necessary adjustments (Mejeh et al., 2024). In this manner, technology supports children in developing independent learning skills and a more comprehensive learning experience (Revishvili & Tsereteli, 2024).

The integration of SRL with AI has the potential to facilitate more personalised and efficient learning experiences for children (Järvelä et al., 2023; Ng et al., 2024). SRL encompasses students' capacity to oversee their learning processes, establish objectives, assess progress, and cultivate strategies, whereas AI provides a range of tools to bolster these processes (Shafiee Rad, 2025). The utilisation of AI facilitates the development of SRL skills by providing feedback, study materials and strategies that are customised to children's learning styles, strengths and weaknesses (Xue et al., 2025). By continuously monitoring students' learning processes, AI-based systems can provide instant feedback and optimise learning strategies by intervening when necessary. Consequently, while SRL processes are managed more effectively, children can have more in-depth learning experiences and strengthen their independent learning skills (Lee et al., 2025). A variety of platforms are currently being established in different countries to provide support in this situation (Chiu, 2024).

The MEBI individualised education portal is a digital platform developed by the Turkey Ministry of National Education (MoNE) to address the individual learning needs of children and enhance the efficacy of the learning process. The portal offers a personalised educational experience, providing access to content tailored to the children's class level, learning speed and interests. The platform also enables children to plan, monitor and assess their own learning processes, with a structure that facilitates the development of SRL skills. By promoting learning through interactive course materials, enhanced content and feedback-oriented assessment tools, MEBI assists students in enhancing their performance in these areas by identifying their areas of weakness. The SRL approach encourages students to take ownership of their learning and develop independent learning skills, thereby increasing their academic success while ensuring equal access to education. Additionally,

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the platform incorporates an AI assistant, known as KANKA (Buddy), which effectively integrates the SRL approach and AI into the teaching process (MoNE, 2024).

1.1. Significance of study

Self-regulation has become a key focus in educational research due to its impact on learning outcomes (Adler et al., 2025). Recent studies (Findyartini et al., 2024; Grüneisen et al., 2023; Hadwin et al., 2025; Jin et al., 2025; Li et al., 2024; Ng et al., 2024; Olí, 2025; Tzimas & Demetriadis, 2024) have focused on the enhancement of individuals' self-regulation skills. A common theme among these studies is the observation and analysis of elements within the classroom environment from the perspective of self-regulation. For instance, Sardi et al. (2025) conducted a study to explore the potential of AI in supporting the development of self-regulation skills.

Technological developments have resulted in the integration of various teaching approaches utilising AI-based applications into education systems (Mazı, 2024). The investigation will explore the potential of AI-based learning platforms to enhance the efficiency of education processes by leveraging the role of SRL in enhancing individuals' cognitive, affective, and behavioural performances, with a focus on the integration of AI into education (Jiménez-García et al., 2024). Some studies report that in-depth research should be conducted on the transformative role of AI in education and how it contributes to teaching methods, strategies and techniques and students' learning processes (Chen et al., 2024; Mazı & Yıldırım, 2025). As Mazı (2024) notes, understanding the capabilities and limitations of AI-based educational applications is crucial for educational systems to formulate future strategic plans. In this context, studies on the relationship between AI platforms and SRL (Deshmukh & Mehta, 2025; Jin et al., 2025; Lee et al., 2025; Ng et al., 2024; Qin & Wang, 2025), scale development studies examining students' attitudes towards SRL (Sarikaya & Sökmen, 2021; Steinbach & Stoeger, 2018), studies determining attitudes towards AI (Bergdahl & Sjöberg, 2025; Mazı, 2024) contribute to the literature. The extant literature acknowledges significant gaps in the research, given that reflections on AI-based platform use in the context of SRL is a nascent field. There is a need for studies that address the impact of integrating AI with SRL on child attitudes. In the context of technological advancements, there is an increasing imperative to comprehend children's attitudes towards AI-supported SRL. This research meticulously delineates the rationale behind why educators, researchers and policymakers must scrutinise children's attitudes as they utilise this transformative technology to enhance their learning. The discernment of student attitudes and the efficacious design, implementation and utilisation of AI-supported SRL in accordance with ethical principles are hypothesised to exert a pivotal influence on the enhancement of children's academic achievements. In light of these, the study aims to develop a valid and reliable scale for measuring students' attitudes towards the integration of AI in SRL.

RQ. Is the scale of students' attitudes towards self-regulated artificial intelligence learning (SRAIL) a valid and reliable scale?

2. Background

Education is a systematic process that is effective in children's acquisition of knowledge, values and skills (Yıldırım, 2025). Education plays an important role in learners' attitudes towards learning, children's performance and learning outcomes (Díez-Palomar et al., 2020). The definition of attitude refers to the cognitive, affective and behavioural dimensions of individuals towards a particular subject, event or situation (Ajzen, 2014). The cognitive domain of attitude examines individuals' beliefs, thoughts and knowledge about a subject. The affective domain of attitude includes the feelings and emotional reactions of individuals towards a situation (Zhang et al., 2024). In the behavioural domain, the actions and behavioural tendencies of an individual can be viewed as reflecting their attitude (Ajzen, 2014). Research in the domain of education (Alemany-Arrebola et al., 2025) has indicated that children's attitudes towards lessons, teachers and the learning process affect their academic achievement and motivation. Children's attitudes towards learning are also significantly affected by the methods and teaching materials used in lessons (Muñoz-Losa & Corbacho-Cuello, 2025). In this context, innovative approaches offered by developing technologies in the field of education have made children's learning processes effective and interactive (Yadav, 2025). Moreover, the recognition that children may not provide sincere or accurate responses due to various factors has underscored the imperative for the assessment of the implicit component of attitudes (Korkmaz, 2017). In the domain of cognitive field studies, such as psychology and education, explicit attitudes reported verbally or in written form are distinguished from awareness and out-of-control attitudes, which are expressed as implicit attitudes. Innovative approaches grounded in AI have a significant impact on shaping children's attitudes (Mazı, 2024).

The integration of AI within educational settings has precipitated a paradigm shift in learning and teaching methodologies (Dong, 2024). The utilisation of AI has been instrumental in analysing children's distinct learning requirements, thereby customising their educational experiences (Yılmaz, 2024). Moreover, it has been employed to provide real-time feedback to educators, offering insights into the performance of children (Marouf et al., 2024). It also facilitates the adaptation of educational content in response to feedback (Strielkowski et al., 2024). However, the integration of AI into education encounters impediments, including inadequate technological infrastructure and ethical considerations (Alwaqdani, 2024). These factors have the potential to adversely influence the attitudes of educators and students towards the incorporation of AI-based systems (Shahid et al., 2024). It can be argued that the mechanisms that provide data-driven feedback offered by AI-based systems contribute to the development of children's self-regulation skills and have a conscious and strategic role in determining individualised learning needs (Afzaal et al., 2024; Strielkowski et al., 2024).

As a challenging concept to define (Burman et al., 2015), the notion of self-regulation, a subject that has been extensively researched in the field of education, can be defined as the ability to manage emotions and behaviours in the early stages outlined in Bandura's social cognitive theory (Schunk, 2013). This concept encompasses the individual's capacity and readiness to engage in specific behaviours (Bandura, 2014). However, subsequent contributions to the field have expanded the concept to include the regulation of cognitive, motivational and social processes, thereby integrating a more comprehensive framework for understanding emotional, attentional and behavioural regulation (Zeidner & Stoeger, 2019). A plethora of models have been posited for the theoretical framework of SRL. In this direction, Boekaerts, Pintrich and Zimmerman's SRL models are given below.

Boekaerts' (1999) self-regulation theory is stated as an active theory that examines the cognitive and affective skills of the individual simultaneously. In this model, the initial stage involves the establishment of the conditions of the learning environment, with the learner then being enabled to recognise both their internal interests and motivations, as well as the external task requirements and stimuli. In the subsequent interpretation stage, the individual is required to interpret these stimuli in conjunction with their own knowledge and learning objectives. In this process, the functions of mental mapping and meaning-making are employed with great efficacy. In the process of evaluation, the individual determines the utilisation of strategy by posing questions to themselves regarding the information they have interpreted within the contexts of academic achievement and self-perception. Following the evaluation phase, the subsequent goal-setting phase clarifies short and long-term objectives. Goals must be formulated with precision, quantifiable, and grounded in practicality. The final stage, that of implementing the task, involves the process of revising the strategy or goal when necessary by applying the strategies chosen by the individual (Boekaerts & Corno, 2005).

Pintrich's (2004) model posits that SRL is a dynamic and interactive process involving cognitive, affective, motivational and behavioural components. The process under discussion encompasses the establishment of learning objectives and the subsequent identification of strategies in the planning/goal-setting phase. It also includes the monitoring phase, in which cognitive progress and strategy use are evaluated. The third phase is the supervision or control phase, in which individual learning regulation strategies and learning arrangements are considered. Finally, the feedback phase involves the evaluation of learning outcomes, the effectiveness of the strategy used, and the child's motivation in the reflection or evaluation phase. Pintrich (2004) emphasises that in each of these stages, the child's self-efficacy beliefs, attitudes towards the tasks and emotional state affect individual learning performance. SRL has been demonstrated to support autonomous learning by increasing the child's intrinsic motivation, as well as the ability to utilise strategies.

Another model of SRL is Zimmerman's SRL model (Chang & Sun, 2024). SRL strategies, which are considered as performances and processes involving goals, tools and perceptions, are applied in individuals' acquisition of knowledge and skills. Zimmerman's SRL model focuses on Bandura's theory of the interaction between the individual, environment and purposeful behaviour (Zimmerman, 2013). According to this model, individuals are required to monitor their learning processes, assess their participation in the learning process, and evaluate the results they achieve (Panadero, 2017). If the achieved results deviate from the predetermined standards, it is recommended that individuals review their evaluation. Achieved results encompass intrinsic motivation and affective elements. In the initial stage, foresight encompasses self-efficacy, outcome expectations, intrinsic interest or value attributed to the outcome, and the motivation to engage in the task. In the subsequent stage, the individual initiates the task and engages in cognitive processes such as imagination, self-talk, focused attention, and memory. The application of these processes enables the individual to monitor the harmony between the results and the goals. In the third stage, individuals can explain what causes the achieved results (Zimmerman, 1989).

Zimmerman's (1989) and Pintrich's (2004) models of SRL, widely regarded as leading frameworks in educational research, offer significant insights into the cognitive, affective and motivational processes of individuals. The theoretical framework accepted in this field is constituted by Zimmerman's three-stage model (forethought, performance, self-reflection) and Pintrich's four-stage model (planning, monitoring, controlling and reflecting). A critical evaluation of these two models reveals several notable advantages. Firstly, they empower children to manage their own learning processes, which is a significant development in education. Secondly, they support activities aimed at developing self-awareness in children, a crucial aspect of personal growth and development. Finally, they can increase children's motivation to learn, a key factor in effective educational engagement. Furthermore, these two models provide a foundation for designing instruction and developing individualised learning strategies. Boekaerts' model is distinguished from other SRL models by its emphasis on the affective regulation dimension and its assertion that factors such as motivational decline or anxiety underlying learning difficulties should also be considered (Boekaerts, 1999). To develop effective programmes that apply the stages of Boekaerts' SRL approach to teaching environments, it is essential to take into account individual differences and contextual factors. It is important to note that SRL models are not without their limitations. Firstly, it is important to note that these models are based on idealised learner profiles. Nevertheless, the efficacy of these applications for individuals with low self-efficacy beliefs or low motivation is limited. Furthermore, when the approaches adopted in education systems are considered in conjunction with cultural differences and socioeconomic variables, the universality of the SRL models may be called into question.

The SRL encapsulates the inherent capacity of children to autonomously set learning objectives, actively monitor their progress, and adjust their strategies based on reflective insights (Dülger et al., 2025). In contrast, AI has taken on a transformative role in education systems, with data analysis, recommendations for individualisation, and simultaneous feedback to optimise the learning process (Wang & Huang, 2025). AI-based applications such as Khanmigo and MEBI are designed to enhance children's metacognitive skills, including self-assessment, to surmount obstacles to learning motivation, and to optimise behavioural performance (Mazari, 2025). AI-based teaching platforms such as MEBI are hypothesised to augment the effectiveness of SRL by providing the guidance and individual learning content that the child requires in the form of various difficulty levels after analysing the individual performances of children (MoNE, 2024).

AI-supported platforms have some disadvantages compared to SRL (Xu et al., 2025). The risk of the development of a dependency on AI is that it may potentially compromise the autonomy of children in relation to SRL (Klimova & Pikhart, 2025). The resulting technology dependency carries the risk of weakening children's SRL autonomy. Especially when children frequently use the suggestions of the AI-supported learning environment in the decision-making phase for their learning, they cannot effectively manage their capacity to develop strategies for problem solving (Sardi et al., 2025). This situation jeopardises the child's self-motivation and autonomy of self-management skills in the long term (Lin et al., 2025). From an ethical point of view, it is expected that the current role of AI in children's learning process should be a 'supportive tool' and should not turn the child into an autonomous decision-making actor in his/her learning. AI-supported platforms should be designed to be transparent, accountable and open to human supervision so that children can effectively use the basic components of SRL, such as taking responsibility, critical and creative thinking.

3. Method

3.1. Design

To develop a reliable and valid scale to measure high school students' attitudes towards self-regulated AI learning, we grounded the development of the SRAIL scale in the SRL scale, which was in turn based on Zimmerman's SRL model (Eryılmaz & Mammadov, 2017). Carpenter's (2018) process for constructing measurement tools will guide the scale development study. The scale to be developed aims to address students' attitudes towards AI-supported learning environments holistically with its cognitive, affective and behavioural dimensions. The study will provide an in-depth understanding of children's perceptions and attitudes towards the integration of AI into learning processes and will provide important data that will guide practices and interventions in the field of education.

3.2. Sampling

The study's sample comprised 250 high school students from various educational institutions in Ankara, Turkey. We collected data using a simple random sampling technique, a probabilistic method that ensures that every child in the target population has an equal chance of selection. This method is widely recognised for its ability to minimise sampling bias and increase the representativeness of the sample, thereby enhancing the reliability and generalisability of the research findings. In the context of statistical sampling, simple random sampling is defined as a process by which units are chosen entirely by chance, ensuring that each unit is selected with the same probability (Zulnaidi et al., 2024). This rigorous sampling approach was instrumental in achieving the study's objective of accurately capturing and analysing children's attitudes, thus providing a solid foundation for subsequent statistical analyses and conclusions.

The rationale behind the selection of high school students as the sample group is that MEBI, an AI-supported SRL platform, is currently exclusively employed to facilitate the learning processes of high school students. In this direction, it is frequently used in the in-class and after-class learning processes of high school students in the sample group.

3.3. Data collection

Prior to the initiation of the research process, we obtained all necessary ethical approvals with meticulous care to ensure compliance with established research standards. The preliminary version of the scale was submitted to the ethics committee at Çankırı Karatekin University, which conducted a thorough review of the study protocol. Following a comprehensive review, the ethics committee granted ethical approval on 22/01/2025, meeting no: 50, thereby confirming that the study adhered to the required ethical standards. Following these essential procedures, we carried out the study with children through a face-to-face data collection format. This direct interaction facilitated clear communication and allowed for immediate clarification of any uncertainties during the data collection process. We distributed the SRAIL scale to 260 high school students and analysed the data from 250 fully completed scales. We administered the SRAIL scale to a sample of high school students in paper-based form. Subsequently, we analysed the gathered data using SPSS 26, which provided descriptive and inferential statistical analyses, and MPlus 7, which we employed for advanced CFA and structural equation modelling. This comprehensive approach, combining rigorous ethical oversight, direct participant engagement, and the use of advanced statistical software, ensured the overall reliability and validity of the study's findings.

3.4. Content validity

To ascertain the item appropriateness of the SRAIL scale, we consulted two education professors and three field experts. We evaluated the item appropriateness on a scale of 0 to 10 points and found the content validity index (CVI) to be 0.88. Ayre and Scally (2014) posit that CVI scores exceeding 0.80 may be indicative of item relevance. After the completion of the experts' review process, we established a five-point Likert scale comprising 24 items.

3.5. Data analysis

Following these, we ascertained the scale's validity and reliability through the conduction of EFA and CFA on the collected data. EFA facilitates the reduction of numerous variables to a smaller number of factors, thereby enabling the determination of the number and characteristics of these factors (Howard, 2023). In this study, the initial step was to examine the sample size to evaluate the suitability of the data for factor analysis within the scope of EFA. This study was subject to the criteria for the minimum sample size recommended for factor analysis. Moreover, the study with 250 children represents an adequate sample size for a scale comprising 24 items (Muthén & Muthén, 2002). Following the determination of adequate sample size, we subjected the fundamental assumptions (sample size, normality, etc.) to rigorous scrutiny through factor analysis (Howard, 2023). Nevertheless, we reduced the scale to 7 items as a consequence of these not meeting the fundamental assumptions (sample size, normality, etc.). The subsequent table provides a comprehensive overview of the information pertinent to the normality assumption within the context of these fundamental assumptions.

As demonstrated in Table 1, the items on the scale demonstrate a normal distribution (Howard, 2023). The scale items are commensurate with the requirements of EFA in the given context.

Table 1
Normality analysis.

Item	Skewness	Kurtosis
I1	−0.82	0.35
I2	−0.65	0.30
I3	−0.80	0.09
I4	−0.43	−0.80
I5	−0.39	−0.57
I6	−0.46	−0.48
I7	−0.89	−0.04
I8	−0.56	−0.24
I9	−0.63	−0.34
I10	−0.53	−0.15
I11	−0.76	0.12
I12	−0.59	−0.27
I13	−0.42	0.15
I14	−1.14	0.61
I15	−0.95	0.38
I16	−0.54	−0.20
I17	−0.78	0.19

4. Results

4.1. Construct validity

In this part of the study, information about the CFA and EFA of the scale is provided.

4.1.1. EFA

We conducted the research with a sample of 250 children. In this context, the study commenced by examining the suitability of the scale items for EFA. The scale was consequently subjected to both EFA and CFA. Further details concerning the EFA can be found in Table 2.

In the EFA, we employed the maximum likelihood technique and determined that the factorial variances were considerable. EFA revealed two dimensions, with the total variance explained amounting to 41.65 %. Additionally, the KMO test value was determined to be 0.85, and Barlett's Test of Sphericity value was found to be 0.00. We determined

Table 2
EFA results.

No	Item	Factor 1	Factor 2
1	I think that using AI programmes increases my success in the lessons.	0.72	
2	I consider that I benefit from the individualised learning experience offered by AI programmes.	0.64	
3	I think AI programmes make my work more efficient.	0.60	
6	I think AI applications motivate me to focus on my learning goals.	0.55	
5	I encourage me to take responsibility for my learning process through the use of AI.	0.51	
4	I feel less stress while studying thanks to AI tools.	0.50	
8	I think that AI-based feedback improves my learning experience.	0.43	
10	I learn at my own pace with AI programmes.	0.41	
9	I use AI tools to set and monitor my academic goals.	0.37	
14	I think AI applications will improve the quality of my assignments and projects.		0.64
15	AI applications help me to organise my work schedule.		0.63
11	AI offers specialised resources for my learning needs.		0.57
16	I think the use of AI programmes makes my learning processes interesting.		0.56
17	I evaluate my progress towards achieving my goals using AI.		0.50
13	I think that AI applications increase cooperation during group work.		0.45
12	I integrate AI tools into my work as part of my regular work routine.		0.41
7	I analyse topics that interest me in depth with AI tools.		0.39
KMO value and Bartlett's Test of Sphericity		0.85	0.00
Total variance explained		41.65	

the factor loadings threshold as 0.35 and analysed the distribution of the items of the scale into factors. Factor 1 (academic success) emphasised items such as “AI improves my success” (0.72). Factor 2 (study style) emphasised items such as “AI improves the quality of my homework and projects” (0.63). The Scree plot graph of the study, which provides insights into the dimensional structure of the scale, is presented below (Fig. 1).

Upon analysis of the figure, it is evident that the structure of the scale comprises two dimensions. Moreover, upon analysis of the scale's dimensions, it is noteworthy that the first dimension is related to academic success and the second dimension is related to study style. As illustrated in Fig. 2, the scale's dimensions, academic success and study style are associated with Zimmerman's SRL model.

Following the finalisation of the EFA, the scale was subjected to a CFA.

4.1.2. CFA

The present section is concerned with an evaluation of the adequacy of the assumptions underlying the CFA. Subsequently, we conducted an assessment, and the results indicated that the scale met the necessary assumptions for CFA. The findings derived from the analysis conducted in this context are presented in Table 3.

The CFA results indicate that the measurement model demonstrates an overall good fit to the data. The χ^2/df value of 1.87 is well below the threshold of 2, suggesting an excellent fit between the model and the observed data. The CFI of 0.91 and the TLI of 0.90, both meeting or slightly exceeding the acceptable level of 0.90, further support that the model is performing satisfactorily. Additionally, the SRMR and the RMSEA both at 0.05 indicate minimal residuals and a good approximation of the model to the data covariance matrix. With a sample size of 250 children, the analysis benefits from an adequate number of observations. The validity and reliability of the measurement model are supported by these indices when considered collectively (Mazı, 2024). Furthermore, the path diagram from the CFA is presented in Fig. 3.

Following the factor analyses, we determined that 7 items should be removed from the draft scale form, which consisted of 24 items. We made this decision because the items did not comply with the assumptions of the EFA (normality, sample size, etc.). The remaining 17 items were subjected to factor analyses. Following the execution of the factor analyses, we determined that all 17 items were compatible. In light of these considerations, we decided to refrain from removing any additional items. Consequently, we determined that the SRAIL scale provided content and construct validity as a result of the analyses. The SRAIL scale is a valid measurement tool.

4.2. Reliability

The study used a rigorous evaluation of the reliability of the scale, utilising two primary indices: Cronbach's Alpha and CRI. We established Cronbach's Alpha at 0.86, signifying internal consistency among the items, thereby ensuring that the questions consistently gauge the same underlying construct. Concurrently, we also found the CRI value to be 0.86, thereby further reinforcing the scale's stability and reliability. The alignment of these indices not only confirms the robustness of the instrument but also suggests that the items are well-correlated and effectively capture the intended dimensions of children's attitudes towards self-regulated AI learning. The results provide evidence that the scale is a valid and reliable instrument for educational research and can be used with confidence in subsequent analyses (Yıldız, 2023).

5. Discussion

The present analysis demonstrates that the SRAIL scale, a measurement tool designed to assess attitudes towards self-regulated AI learning in children, is consistent with established methodological approaches to the evaluation of attitude scales (Köse et al., 2025; Luo & Zou, 2025; Saleem et al., 2025). Furthermore, the SRAIL scale represents a pioneering development in the field of scale construction, as it is the first study to integrate the concepts of AI and SRL. The primary objective of this study is to ascertain the attitudes of students in this particular field. Consequently, it is regarded as a significant and valuable addition to the extant literature on self-regulated AI learning.

The SRAIL scale comprised two dimensions. The initial dimension was designated “academic success”, while the subsequent dimension was entitled “study style”. The academic achievement dimension is indicative of factors such as students' course performance, their success

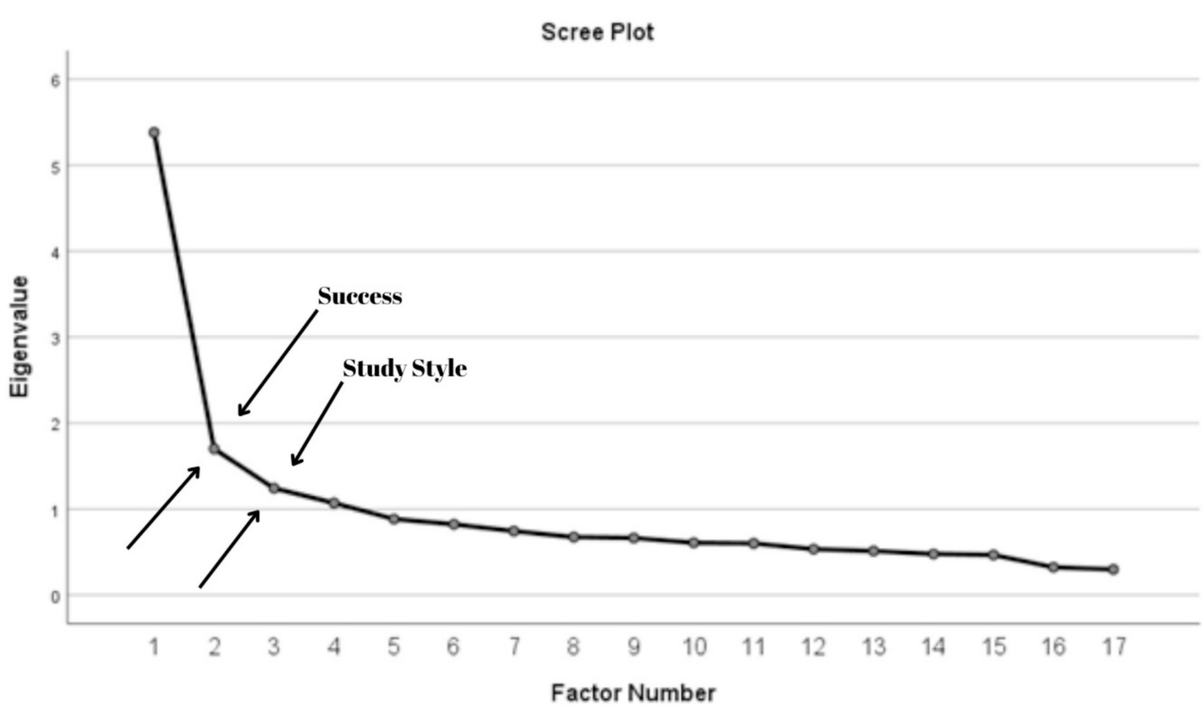

Fig. 1. Scree plot.

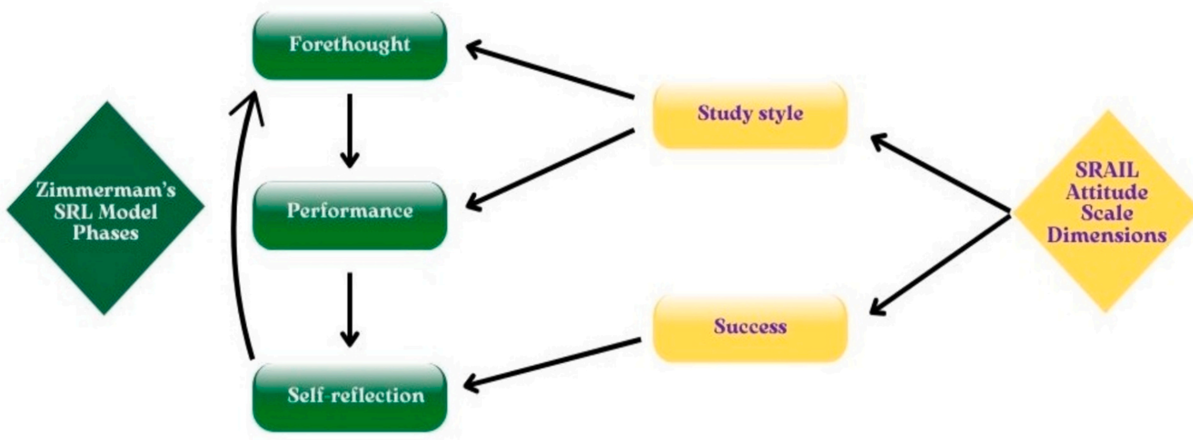

Fig. 2. Model and dimension mapping.

Table 3
Results of CFA.

Index	Value	Result (Fit)
χ^2/df	1.87	Good
CFI	0.91	Acceptable
TLI	0.90	Acceptable
SRMR	0.05	Good
RMSEA	0.05	Good
Participants	250 Children	Adequate

in examinations, and their effectiveness in achieving their objectives. Conversely, the study style dimension encompasses characteristics such as children's approach to the learning process, time management, strategy use and level of preparation for lessons. Integrating these two dimensions facilitates a comprehensive assessment of students' academic performance, complemented by an assessment of their attitudes and behaviours related to the learning process. The development of the SRAIL scale necessitated meticulous deliberation on the interaction between SRL processes and the feedback and individualised learning contents provided by AI. The meticulous design of this programme is intended to ensure that the learning content is both efficient and engaging. A review of the extant literature on this topic reveals several important cases. For instance, in Ng et al.'s (2024) study, which employed ChatGPT developed using the findings of Zimmerman and Schunk's (2011) study, an enhancement in self-regulated AI learning among secondary school students in Hong Kong was observed concurrently with an improvement in their academic achievement in science. Furthermore, Jin et al. (2025) concluded that children who engaged in self-regulated AI learning increased their academic writing proficiency. In a similar vein, Deshmukh and Mehta's (2025) study found that individuals' self-regulated AI learning contributed to the development of organisational culture. In a separate study, based on Zimmerman's (2000) SRL model and supported by a chatbot, it was determined that university students' motivation for learning, learning performance and reflection increased (Lee et al., 2025). A review of research on study style reveals the utilisation of Zimmerman's SRL model from a cognitive perspective in the study conducted by Qin and Wang (2025). In addition to academic achievement in mathematics, the study investigated time management, confidence, interest and anxiety related to mathematics from study styles. Furthermore, the study examined the SRL components of memory, deepening and control strategies. It was hypothesised that the achievement of students in mathematics would increase in line with the adoption of an appropriate study style. In their study, Alvandi et al.

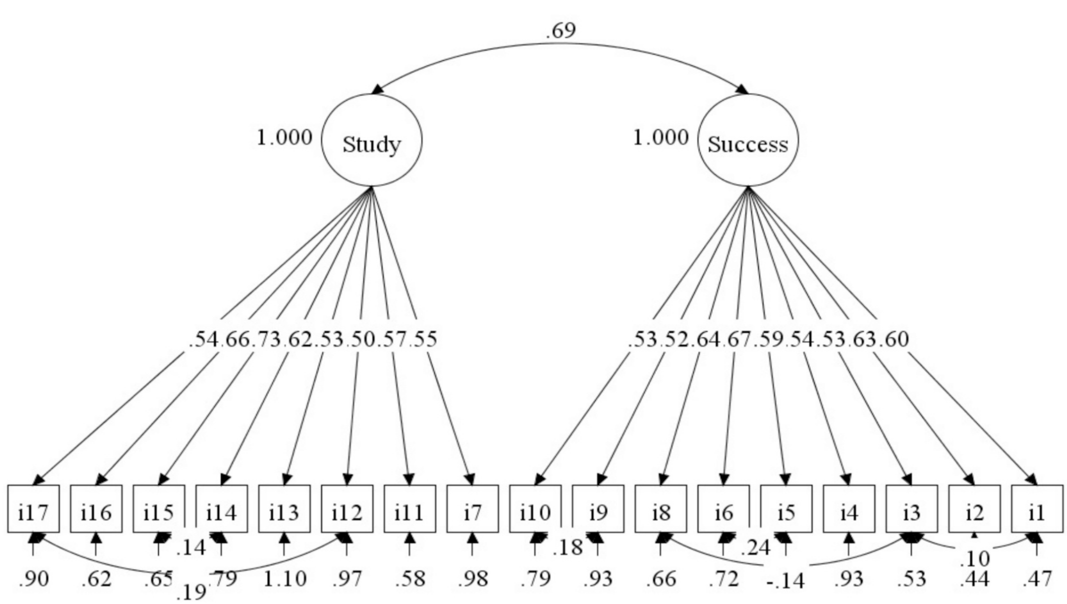

Fig. 3. Path diagram.

(2025) utilised a range of SRL strategies in a research investigation conducted with EFL students in Iran. The conclusion drawn from this analysis was that the utilisation of diverse study styles led to an enhancement in their speaking abilities, attributable to a reduction in their anxiety about speaking. In Steinbach and Stoeger's (2018) study on teachers' attitudes towards SRL, the structure of the scale was determined as seven-dimensional. They determined that the scale in question, which was adapted into Turkish by Sarikaya and Sökmen (2021), had seven dimensions. Furthermore, the development of this scale was informed by the SRL model proposed by Ziegler and Stoeger (2005). The present situation is incongruent with the findings of the research conducted based on a different sample group. In their study, Jin et al. (2025) sought to ascertain the perceptions of university students regarding AI-supported SRL in the context of online learning through the utilisation of interviews, employing Zimmerman's SRL model as a theoretical framework. The study revealed a neglect of attitude in favour of the cognitive and metacognitive dimensions of SRL. The present study differs from the results of the previous study. A prevailing theme in extant literature pertains to the notion that AI possesses the capacity to function as a potent instrument in the realm of personalised learning. The findings of this study demonstrate that the strategic implementation of SRL by educators is imperative to ensure that it complements rather than replaces core cognitive abilities. The majority of previous studies demonstrate a high degree of consistency with the SRAIL scale developed in this research.

To understand the impact of AI addiction on the continuous use of AI-based platforms in the SRAIL scale, we hypothesised that the long-term correction of errors made by children in the self-evaluation process by AI negatively affects the decision-making mechanism of the child's SRL process. The study determined that long-term AI-based learning environments have a detrimental effect on the transformational nature of children's SRL process (Lin et al., 2025). Furthermore, Sardi et al. (2025) emphasised the potential of generative AI to enhance SRL and critical thinking, thus pointing to a significant shift in educational practices. However, it should be noted that the study warned against over-reliance on technology and underlined the need to strike a balance between AI integration and the development of children's independent thinking skills. This finding highlights the congruence between the research in the extant literature and the SRAIL scale.

5.1. Conclusion

In this study, we developed a valid and reliable scale (SRAIL) for use in different cultures to measure attitudes towards self-regulated AI learning in children. The SRAIL scale was compatible with Zimmerman's SRL model, and AI was used in the application. The SRAIL scale had two dimensions. The first dimension measures students' academic achievement, while the second dimension is named 'study style'. The SRAIL scale ascertains that "long-term" AI-supported SRL has a detrimental effect on students' decision-making mechanisms.

5.2. Suggestions for future studies

In subsequent research, it is imperative to ascertain the generalisability of the developed scale by applying it to diverse demographic groups and cultural contexts. In this direction, it is necessary to evaluate the universality of the scale and its consistency among various student groups with samples from different geographical regions, socioeconomic levels and educational levels. Conversely, the conduct of long-term follow-up studies to understand how students' attitudes towards self-regulated AI learning evolve is an important area of research. This will allow a more comprehensive study of the impact of digital transformation and technological developments on educational processes, together with changes in students' attitudes. It is particularly the case that the effects of distance learning and hybrid model applications in the post-pandemic educational environment can be revealed more clearly with such studies. Furthermore, we recommend that the existing items of the scale be subject to regular updates and, when necessary, restructuring in light of technological and pedagogical advancements. In light of the rapid shifts observed in students' learning strategies and technology usage habits, adapting the scale to reflect a dynamic structure is imperative to ensure the validity of the measurement tool. Moreover, the application of mixed methods research supported by qualitative research methods, in addition to quantitative data analyses, will allow for a more in-depth interpretation of the results. This methodological approach will facilitate a more in-depth understanding of the complex relationships between children's attitudes and learning processes, providing strategic insights for educational practitioners and policymakers. Finally, we recommend the utilisation of AI-powered applications such as MEBI to enhance the educational process. These programs facilitate the development of self-regulation skills by offering personalised learning experiences.

5.3. Limitations

The SRAIL scale is limited to the responses of the students attending two high schools in Ankara who used AI-supported SRL platforms in their courses. It is also limited to the attitudes and prejudices of the students participating in the study towards AI and SRL. Moreover, the potential social desirability effect of the students' responses to AI constitutes a limitation of this study. Self-reported attitudes may not fully capture behavioural engagement with AI tools. In Turkey, the utilisation of AI-supported SRL platforms has recently gained popularity. Nevertheless, this is a limitation in countries where AI-supported learning platforms are not utilised effectively and traditional cooperative learning is practised. We developed the scale in question in Turkey. However, we translated the items of the scale into English with the help of a language expert. This facilitates the transposition of the SRAIL scale to other countries. The SRAIL scale is subject to limitations in its application across different languages, owing to its conceptual limitations when translated. Furthermore, the construct validity of the scale has not been assessed in different age groups or educational levels. Conversely, the items of the SRAIL scale constitute a general scale for determining the attitudes of students at all levels using AI-supported SRL platforms. We intended the SRAIL scale for deployment in teaching environments that possess a technological infrastructure deemed suitable for the integration of AI. In this context, individualised learning environments assume particular significance.

CRediT authorship contribution statement

Ayşegül Mazı: Methodology, Funding acquisition, Data curation, Investigation, Formal analysis, Conceptualization. **Ali Mazı:** Writing – review & editing, Visualization, Supervision, Resources, Writing – original draft, Validation, Software, Project administration.

Ethical approval

The research was approved by the Çankırı Karatekin University ethics committee on 22/01/2025, with meeting no:50.

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Declaration of competing interest

Authors states that there isn't conflict of interest.

Appendix A

No	SRAIL Student Attitudes Scale
1	I think that using AI programmes increases my success in the lessons.
2	I consider that I benefit from the individualised learning experience offered by AI programmes.
3	I think artificial intelligence programmes make my work more efficient.
4	I feel less stress while studying thanks to AI tools.
5	I encourage me to take responsibility for my learning process through the use of AI.
6	I think AI applications motivate me to focus on my learning goals.
7	I analyse topics that interest me in depth with AI tools.
8	I think that AI-based feedback improves my learning experience.
9	I use AI tools to set and monitor my academic goals.
10	I learn at my own pace with AI programmes.
11	AI offers specialised resources for my learning needs.
12	I integrate AI tools into my work as part of my regular work routine.
13	I think that AI applications increase cooperation during group work.
14	I think AI applications will improve the quality of my assignments and projects.
15	AI applications help me to organise my work schedule.
16	I think the use of AI programmes makes my learning processes interesting.
17	I evaluate my progress towards achieving my goals using AI.

Data availability

Information on all the data from this research will be made available on request by contacting the corresponding author.

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