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The Impact of 6+1 Traits of Writing Model On Seventh-Grade Students' Fairy Tale Writing Skills and Writing Attitudes: A Mixed Methods Study

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Abstract

Previous research highlights the positive effects of the 6+1 traits of the writing model on students' general writing skills; however, its impact on fairy tale writing remains unexplored. This study examines how the 6+1 traits of the writing model affect seventh-grade students' fairy tale writing skills and attitudes. The study group comprised 43 seventh-grade students from a public school in the 2022-2023 academic year. A quasi-experimental design with a control group was used for the quantitative phase, while a case study approach was adopted for the qualitative phase. The experimental group received instruction based on the 6+1 traits writing model, whereas the control group followed traditional methods. Data were collected through the 6+1 analytical writing and assessment scale, a writing attitude scale, and semi-structured interviews. Quantitative analysis, including descriptive statistics and hypothesis tests, revealed that the 6+1 traits writing model significantly improved students' fairy tale writing skills (d = 1.15) and writing attitudes (d = 1.57). Qualitative findings supported these results, with students reporting enhanced writing abilities and motivation. Based on these findings, the study recommends integrating the 6+1 traits of the writing model into middle school writing instruction to foster both skill development and positive writing attitudes.

Keywords: 6+1 traits of writing model, Fairy tale writing, Turkish education, Writing attitude

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Introduction

Rapid technological progress and globalization have profoundly affected individuals' social, economic, and cultural lives, reshaping individual identities and transforming the social structure. In this rapidly changing world, individuals must constantly redefine their identities and lifestyles. In this process, education has become an important tool that provides individuals with the competencies they need, such as technological competence, creativity and innovation, adaptability, global citizenship, digital literacy and social-emotional skills, while at the same time contributing to the discovery of their potential and personal development (Eğmir & Çengelli 2020; Ertem, 2024; González-Pérez & Ramírez-Montoya, 2022; Partnership for 21st Century Skills, 2015; Van Laar et al. 2020). The education of basic language skills plays an important role in acquiring these skills by education.

The idea that human beings are social beings is a reality that has been accepted throughout history (Aronson & Aronson, 2011). The most obvious indicator of this situation is his/her use of language. The structure, function, and learning processes of language, which have been the focus of philosophers, linguists, and educators for centuries, have been a subject of curiosity throughout history. Chomsky's (2001) view that language is a tool that has the power to create an unlimited variety of meanings with a limited vocabulary emphasizes the creativity and productivity of language. These features of language are present in communication and in shaping thought, facilitating learning, and mediating the way individuals make sense of the world. Therefore, it is clear that mastering language means mastering mental skills. Chomsky's (2001) metaphorical statement that language is the mirror of the human mind can be considered within this framework. Vygotsky (1978), one of the prominent researchers in the field of language, argued that language is intertwined with thought and that language development supports cognitive development. These definitions emphasize the close relationship between language and the mind and its multifaceted impact on the development of the individual.

Listening and reading skills are defined as language skills for comprehension while speaking and writing skills are defined as language skills for expression (Eliason & Jenkins, 2003; Ezell & Justice, 2005). Writing, which is one of the language skills for expression, is a versatile skill that assumes an important function in the development of new competencies that lifelong education aims to provide individuals with, is the most difficult and the last skill acquired, and contributes significantly to the permanence of knowledge (Bazerman et al., 2017; Özdemir & Özbay, 2016; Ruhama & Purwaningsih, 2018). According to Başkan and Ustabulut (2020), writing doesn't only consist of correctly encoding and analyzing sounds and words; it also includes the competencies of organizing thoughts, structuring meaning, choosing appropriate words, and organizing content for a specific purpose. Understanding language requires using different skills such as listening, reading, visual reading, and expression skills (speaking, writing, visual presentation). In addition to mental processes and skills, writing also requires physical, visual, and perceptual skills to be included in the coordination of the mental process.

The Turkey Century Education Model, which includes the updated Turkish Curriculum, is a comprehensive approach that aims to transform the Turkish education system according to the needs of the age. The main objectives of this model are to equip students with the skills of the 21st century and to raise them as creative individuals, critical thinkers, and problem solvers. In this context, the Ministry of National Education [MNE]

(2024) reshaped its policies on teaching writing in the Turkey Century Education Model. According to this model, writing improves students' ability to organize their thoughts, expression skills, and communication skills. According to the philosophy of this model, the teaching of writing is considered on the axis of an interdisciplinary understanding. Accordingly, students develop the ability to synthesize and analyze information from different disciplines. Writing skill is considered an important learning area in the Turkey Century Education Model (MNE, 2024).

The success of the studies conducted in schools to improve students' writing skills is closely related to selecting the proper teaching methods. Writing teaching models based on student-centered, multifaceted approaches that consider students' interests significantly contribute to developing writing skills by enabling students to be active in the writing process, set personal goals, and evaluate their work regularly. In this framework, teachers are expected to research effective teaching methods and techniques in the classroom. In contrast, students are expected to develop both knowledge and language skills by reinforcing the knowledge they have acquired in the language learning process through various stages (Srimunta et al., 2020; Şahbaz, 2013). The 6+1 traits of the writing model, which includes idea, organization, word choice, style, sentence fluency, spelling, and presentation dimensions of writing, is thought to be one of the models that will meet this expectation (Culham, 2010; Gillespie & Graham, 2014; Karakoç Öztürk, 2021; Maynard & Young, 2022).

6+1 Traits of Writing

The 6+1 traits of the writing model were created by researchers at the Northwest Regional Educational Laboratory (NWREL) in the USA in the 1980s, including the essential characteristics a qualified writer should have (Culham, 2010). With these aspects, the model effectively solves the problems experienced in writing education today. It has been proven in many previous studies that the 6+1 traits of the writing model are one of the most practical ways to overcome the obstacles encountered in writing education (Altuner Çoban & Ateş, 2022; Kalsum et al., 2020; Maynard & Young, 2022; Qoura & Zahran, 2018; Sağlam, 2022; Un-udom, 2020; Zahran, 2018).

Fairy Tale

Individuals should be introduced to original texts in different genres and forms from the first years of their education life; these texts should have features that allow children to develop their creativity in language by taking them as models in writing activities (Sever, 2015). According to Bakken and Whedon (2002), individuals first meet event-based texts in childhood, in the family environment. Among these texts, fairy tales play a critical role, especially in language development. In this context, one of the effective text types is fairy tales (Bağcı Ayrancı & Mete, 2019; Çetinkaya et al., 2019). Fairy tales, which are indispensable parts of cultural heritage, entertain children and contribute to developing their cognitive, emotional, and social skills (Vygotsky, 1978; Helimoğlu Yavuz, 2002). At the same time, the fairy tale is a profound source that develops children's imagination, creativity, and expression skills, allowing them to produce original stories and discover the depths of their inner worlds. For this reason, fairy tale writing activities support children's language development, expand their vocabulary, give them the ability to narrate events sequentially, and help them meet different perspectives (Oğuzkan, 1997; Yalçın

& Aytaş, 2012; Yavaş Çelik & Yavuz, 2017). In this context, it is stated that fairy tales will effectively teach writing skills (Karatay, 2007; Sever, 2015; Türkben, 2018). In addition to its linguistic functions, according to the sociocultural learning theory, it teaches children moral values. It develops their ability to empathize (Bettelheim, 1976). With these aspects, fairy tales play an important role in education and individual development. They are a text type that should be emphasized in curricula (Buch, 1992).

Purpose of the Study

This study examines how the 6+1 traits of the writing model affect seventh-grade students' fairy tale writing skills and attitudes. Previous research has demonstrated the model's positive effects on students' writing skills across various educational levels. However, its impact on fairy tale writing remains unexplored. While studies have shown improvements in writing success—particularly in idea development, organization, style, and spelling rules—certain aspects, such as word choice and sentence fluency, have shown limited progress (Kalsum et al., 2020). Moreover, the model has been found to enhance critical thinking and writing skills at the university level (Qoura & Zahran, 2018) and positively influence writing achievement and attitudes in EFL contexts (Un-udom, 2020). At the primary school level, it has significantly improved writing success (Maynard & Young, 2022). It has been particularly beneficial when integrated with intertextual reading for gifted students (Sağlam, 2022). In addition, the effect of the model on the writing skills of students with special needs was also investigated. Rowland et al. (2020) examined the difficulties encountered by students with disabilities in writing processes using the 6+1 traits of the writing model. They discussed technologies that can support the development of these skills. In addition, it was determined that the model, combined with blended learning and modeling.

Beyond cognitive gains, previous studies indicate that the 6+1 traits of the writing model also influence affective factors related to writing, such as self-efficacy and writing anxiety (Altuner Çoban & Ateş, 2022; Görgüç, 2016; Özdemir & Özbay, 2016; Un-udom, 2020). While positive effects have been observed in both pre-service teachers and sixth-grade students, no study has specifically examined its impact on the writing attitudes of seventh-grade students. To address this gap, a fairy tale writing instruction program was developed based on the 6+1 traits of the writing model, aiming to enhance writing skills and attitudes within a school setting. By aligning fairy tale elements with the dimensions of the model, this study provides a structured approach to writing instruction that can guide students in generating creative ideas, expressing them effectively, improving fluency through original word choices, applying spelling rules accurately, and presenting their texts visually in an engaging manner. Additionally, it is expected that students will gain a deeper understanding of the fundamental characteristics of the fairy tale genre while developing language awareness and a shared understanding of written expression.

In the study, answers to the question 'What is the impact of 6+1 traits of writing model on seventh-grade students' fairy tale writing skills and writing attitudes?' and the following sub-questions were sought about this question:

1. What is the impact of the 6+1 traits of writing model on seventh grade students' fairy tale writing performance?
2. What is the impact of 6+1 traits of writing model on seventh grade students' writing attitudes?

3. What are the opinions of the experimental group students about the experimental application process after the application?

Method

Research model

In this study, an exploratory mixed-method design was used. The exploratory sequential design aims to enrich the statistical results obtained with quantitative data from a sample by analyzing them in-depth with qualitative data (Creswell & Plano Clark, 2014). In this design, which follows a two-stage process, quantitative data that can directly answer the research question are first collected and analyzed. In order to better understand and deepen the findings of this first stage, qualitative data collection and analysis methods are used in the second stage (Figure 1).

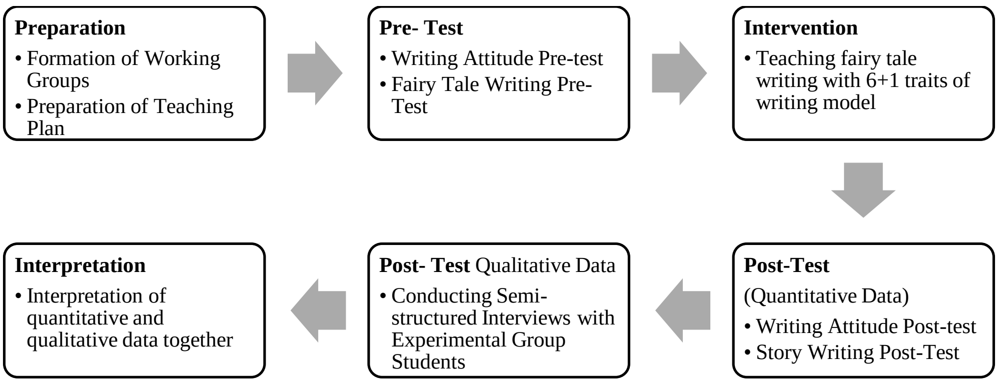

Figure 1. Research Plan

Working Group

In this study, the convenience sampling technique, a subset of purposive sampling methods, was employed to select the study group. As a non-random sampling approach, purposive sampling enhances research efficiency and practicality while enabling an in-depth investigation by focusing on information-rich cases aligned with the study's objectives (Büyüköztürk et al., 2018; Yıldırım & Şimşek, 2016;). The fact that the researcher worked in the same institution as the study group students ensured that the experimental process steps were quickly implemented and that the subsequent interviews were conducted healthily. In order to observe whether the classes had similar characteristics, the students' Turkish averages of the previous year were examined. One of the two classes that did not differ significantly in this criterion was assigned as the experimental group and the other as the control group. The comparison of the scores of the groups is shown in Table 1.

Table 1. Comparison of year-end Turkish language averages of the groups

	Group	N	M	Ss	t	p
End of Year Turkish Course Grade Averages	Experimental	22	93.091	1.563	.292	.772
	Control	21	93.184	1.702	.291	.758

An analysis of the previous year's Turkish language averages for both groups revealed no statistically significant difference between the students' scores. Based on these findings, both classes were at a comparable level before the implementation.

A maximum diversity sampling method was used to determine the students who were interviewed for the qualitative dimension of the research. In this sampling method, the sample is determined according to different categories that are at a similar level within themselves related to the research problem. The purpose of maximum diversity sampling is to ensure diversity and to determine what kind of standard or similar aspects exist between diverse situations (Yıldırım & Şimşek, 2016). In this direction, interviews were conducted with 12 volunteer students with low (4), medium (4), and high (4) mean scores from the post-tests of the research. Table 2 presents the codes assigned to the interview group students and their scores from the post-test assessing their fairy tale writing skills. The codes of the students interviewed for writing fairy tales are shown in Table 2.

Table 2. Post-test Scores of the Interviewed Students for Writing Fairy Tales

Student	L1	L2	L3	L4	M1	M2	M3	M4	H1	H2	H3	H4
Post Test Total Score	8	11	13	13	18	20	22	23	29	31	35	35

Data Collection Tools

As part of the research, the researcher utilized three distinct data collection tools to gather both quantitative and qualitative data. To collect quantitative data, the 6+1 Analytical Writing and Assessment Scale, adapted for Turkish lessons by Özkara (2007), and the Writing Attitude Scale for Secondary School Students, developed by Can & Topçuoğlu Ünal (2017), were employed. Based on the quantitative findings, a semi-structured interview form designed by the researcher was used to obtain qualitative data and explore the quantitative results in greater depth.

6+1 Analytical Writing and Assessment Scale

The 6+1 analytical writing and assessment scale was developed by researchers at the Northwest Regional Educational Laboratory (NWREL) in the USA in the 1980s based on the writing model of the same name (Özkara, 2007). This scale, which the researchers developed with the help of teachers in Beaverton and Oregon, includes the features that should be present in quality writing and the criteria to be considered in measuring these features (Grundy, 1986). According to the scale, the features that should be present in good writing are grouped under seven headings: ideas, organization, style, voice, word choice, sentence fluency, spelling and punctuation, convention, and presentation (Özkara, 2007). In Turkey, Özkara (2007) adapted this scale into Turkish by taking expert opinions. The scale's reliability was calculated as 0.92 for the ideas dimension, 0.91 for the organization dimension, 0.89 for the style dimension, 0.91 for the word choice dimension, 0.90 for the sentence fluency dimension, 0.93 for the spelling dimension, and 0.92 for the presentation dimension. The fairy tales written by the students before the research, during the application studies, and at the end of the research were evaluated by the researcher and two experts by considering the criteria on the scale. When scoring, the lowest score for each scale dimension is 1, and the highest score is 5. Depending on the nature of the dimension analyzed in writing, 1,2,3,4, and 5 points can be given for each dimension (Culham, 2010; Werkmeister, 2010).

Writing Attitude Scale for Secondary School Students

In order to develop the scale, Can and Topçuoğlu Ünal (2017) applied the draft of the structure created with expert opinions to 334 students at the secondary school level. The Kaiser-Meyer-Olkin value of the scale was 0.840, and Bartlett's Sphericity Test value was (X^2=2397,063; df=703, p<.000). According to the exploratory factor analysis, the scale has a structure consisting of 23 items under three factors. Ten items were categorized under the 'interest,' six under the 'perception', and seven under the 'contribution' factor. The total variance ratio of these three factors for the scale is 43.7%. The structural compatibility of the three-factor scale was assessed through confirmatory factor analysis. The goodness-of-fit index values (X^2=497.54, RMSA=0.097, GFI= 0.75, SRMR= 0.091, CFI= 0.79, NNFI= 0.76, RMR= 0.071) indicated that the scale demonstrated construct validity. As a result of Cronbach's Alpha analysis, it was observed that the reliability coefficient was 0.891. These data concluded that the scale met the validity and reliability criteria and could be used in educational research (Can & Topçuoğlu Ünal, 2017).

Semi-structured Interview Form

In the study, the researcher prepared a semi-structured interview form by taking expert opinions to evaluate in detail the impact of fairy tale writing training on students' fairy tale writing skills and writing attitudes according to the 6+1 traits of the writing model. Semi-structured interviews offer ease of analysis with a combination of fixed options and open-ended questions, allowing participants to express themselves and contribute to the process of collecting in-depth information (Büyüköztürk et al., 2018). In the form, eight questions were prepared to be asked of the identified students (Table 3). In order to ensure content validity, the draft interview form, the experimental implementation plan, and the quantitative data collection tools used were shared with three experts in the field. The compatibility of these tools and the interview form was evaluated. The interview form was edited and finalized per the experts' feedback. The interview form was deliberately omitted before the application to avoid influencing students' perceptions of the study. However, the interview questions also included questions about their pre-study situation. In the interviews, qualitative data were obtained from the students' opinions about the 6+1 traits of the writing model, fairy tale writing activities, and writing. Quantitative data was tried to be explained in more depth through these data.

Table 3. Interview Questions

Q1	How did the story writing training through the 6+1 traits of writing model affect your thoughts and attitudes towards writing?
Q2	What does the 6+1 traits of writing model remind you of?
Q3	What do you think about the effects of 6+1 traits of writing modelled fairy tale writing training on your writing skills? Write the positive or negative sides.
Q4	How did the fairy tale writing training with the 6+1 traits of writing model affect your writing habits?
Q5	What effect did the 6+1 traits of writing modelled story writing training have on your writing anxiety?

Q6	After the story writing training with the 6+1 traits of writing model, how do you feel when you start a new writing (anxious, self-confident, enjoyable, motivating, I write with love, etc.)?
Q7	After the fairy tale writing training with the 6+1 traits of writing model, do you think that you consciously use the rules of the fairy tale genre while writing a fairy tale?
Q8	Can you tell us about the language and expression features you used in the tales you wrote after the application?

Research Implementation

The implementation process took place over 12 weeks, including pretest measurements, a training plan for fairy tale writing based on the 6+1 traits of the writing model, and post-test measurements. For each dimension of the 6+1 traits of the writing model, two lesson hours of instruction were planned per week. For each dimension of the 6+1 traits of the writing model, two lesson hours of instruction were planned for one week. The experimental implementation process of the research was planned in two stages: the pre-experimental and experimental processes. Before the experimental process, the procedures for the ethics committee permission were initiated, and after all the necessary permissions were obtained, the research planning was completed, and the pretest application phase was started. A story writing teaching program was created with 6+1 traits of the writing model. Then, the data related to the pretests were collected from the students in the experimental and control groups. Afterward, the experimental process started. The program is shown in detail in Table 4.

Necessary permissions were obtained from the relevant institutions and organizations for the research. Two classes with similar Turkish grade point averages from the previous year were selected as the study group at the secondary school where the study took place. One of these classes was designated as the experimental group, while the other served as the control group. The relevant people were informed about the research. At the beginning of the research, pretests of fairy tale writing and writing attitudes were applied to the experimental and control groups. In the implementation phase of the research, the students in the experimental group were presented with the content of 6+1 traits of the writing model and fairy tale writing instruction by considering the lesson plans prepared by the researcher beforehand.

At this point, the researcher assumed the role of the course instructor for the experimental group. In contrast, the control group received instruction through traditional teaching methods. In the last step of the research, the post-test of fairy tale writing and writing attitude was applied to the experimental and control groups. In the study, interviews were conducted with the students of the experimental group using a semi-structured interview form in order to reveal the students' opinions about the applications with the experimental group, which were carried out with the experimental group with the content of fairy tale writing education with 6 + 1 traits of writing model. The data collected were analyzed with the help of SPSS 26.0 software.

Table 4. 6+1 Traits of Writing Modelled Fairy Tale Writing Training Plan

Sessions	Purpose	Activity
1st Session: Ideas	Writes clear and focused texts that do not distract the reader's attention. Enriches the main idea with appropriate ideas and details.	• Environmentalist Fairy Tale Heroes
2nd Session: Organization	The student transfers the organisation of the writing by developing the main idea and the subject.	• Sorting paragraphs and sentences given in mixed order • Filling in the blank section or sections
3rd Session: Voice	He writes as if he is talking to the reader.	• What is your style? One colour, An animal, A season A type of food, Your favourite outfit A facial expression • Evaluation of the styles of different artists singing the same song
4th Session Word Choice	He/she chooses words that will convey the desired message in his/her writing in a complete, interesting and natural way.	• Two different examples of the same news text written in different words.
5th Session: Sentence Fluency	He writes in perfect harmony, harmony and fluency.	• Evaluation of different fairy tale texts in terms of fluency • Writing fluent sentences
6th Session: Conventions	Uses spelling and punctuation rules in his/her writing in a way that facilitates reading and understanding the text.	• Applying spelling and punctuation rules on a fairy tale • Correcting spelling and punctuation mistakes
7th Session: Presentation	The format and presentation of the text should be such that it is easy for the reader to understand and integrate the message.	• Story Writing Activity

Data Analysis

The study's quantitative data were scored using the 6+1 traits of the writing model scale with the contribution of two experts after the tales written by the students had been collected. In the Kendall W analysis to reveal the inter-rater agreement, it was determined that the agreement coefficient of the expert group was .87. The ideal value of the Kendall W agreement coefficient is the closest value to 1 in the range of 0-1. When the value to be obtained is greater than .80, it can be said that the reliability between the raters is ensured; in addition, the p-value being less than .05 indicates a significant degree of agreement (Can, 2019). Since there was no problem with inter-rater agreement, the average of the scores given by the three raters was considered to determine the students' fairy tale writing levels in the analysis process. Then, whether the data were normally distributed was evaluated with skewness, kurtosis values, and the Shapiro-Wilk test. In this study, the range of -1.5 to +1.5 was taken as a reference for skewness and kurtosis coefficients, as Tabachnick and Fidell (2013) suggested. Since the number of students in the experimental and control groups before and after the implementation of the study was below 30, the Shapiro-Wilk Test was used in normality calculations. According to the data distribution, unrelated samples, paired samples, a t-test, and a Mann-Whitney U test were used. All analyses accepted the confidence interval as '95%' and the significance level as .05.

A semi-structured interview form prepared by the researcher was used to answer the sub-question of the study: 'What are the opinions of the experimental group students about the fairy tale writing training process organized with 6+1 traits of the writing model after the application?'. All interview data were coded thematically, and qualitative data analysis was performed. Coding can be defined as dividing data into different categories by dividing them according to specific characteristics, and thematic coding consists of examining the data and bringing together those with similar characteristics (Corbin & Strauss, 2008). The codes gathered were organized into specific categories, which were subsequently grouped into various themes. Based on the answers received from the interviewed students, a total of three themes (Cognitive Characteristics, Affective Characteristics, Language and Expression Characteristics), four categories (Knowledge, Skill, Attitude, Perception), and 32 codes (e.g., Love of writing, knowledge of rules, fluency) were determined. The interviewed students were given pseudonyms from T1 to T12 during this process.

Inter-coder reliability plays a critical role in the analysis of interviews because when reliability is not ensured, the interpretations obtained lose their validity (Lombard et al., 2002). The agreement between the coders was assessed to enhance the reliability of the qualitative data analysis. The first coder was the researcher who conducted the study, and the second coder was an expert who also evaluated the questions in the interview form and had a good command of the field. In order to calculate the agreement between the coders, the formula developed by Miles and Huberman (1994), also known as the percentage of agreement, was used. For this study, the result of the calculation made with the aforementioned formula was determined to be 82%, which means that the reliability level of the qualitative part of the study is high.

Results

The results of the study consist of two parts. In the first part, 7th grade students' fairy tale writing and writing attitude levels were evaluated using descriptive statistics with quantitative data analysis method. In the second part, a qualitative approach was used to obtain in-depth information about the increase in students' fairy tale writing scores and writing attitude levels.

Quantitative Findings

For the first sub-question of the study, "How does the 6+1 traits of writing model affect seventh grade students' fairy tale writing skills?", a comparison was made between the pre-test and post-test scores of the experimental group students in terms of their fairy tale writing abilities. T Test for Related Samples was used to compare the pre-test and post-test scores of the experimental group regarding fairy tale writing skills and the findings are presented in Table 5.

Table 5. Comparison of Pre-test and Post-test Mean Scores of the Experimental Group Regarding Fairy Tale Writing Skills

	Groups	N	M	Sd	t	p	d
Fairy Tale Writing Skills	Experiment Pre-test	22	21.135	5.665	-8.399	.0002	1.29
	Experiment Post-test	22	27.878	4.719			

Based on the results in table 3, the paired samples t-test, performed to assess if there was a significant difference in the total pretest and posttest scores of the experimental group students' fairy tale writing skills, revealed a notable difference between the mean pretest score (M =21.135) and the mean posttest score (M =27.878) (p= .0002, p<.05). This result indicates that the experimental study using the 6+1 traits of writing model demonstrated a statistically significant improvement in the fairy tale writing success of the experimental group.

T Test for Related Samples was used to compare the pretest and posttest scores of the control group regarding fairy tale writing skills and the findings are presented in Table 6.

Table 4. Comparison of Pre-test - Post-test Mean Scores of the Control Group Regarding Fairy Tale Writing

	Groups	N	M	Sd	t	p	d
Fairy Tale Writing Skills	Control Pre-test	21	22.397	6.899	.873	.393	0.11
	Control Post-test	21	21.667	5.967	4.324		

As seen in table 4, according to the data of the paired samples t test conducted to determine whether there was a significant difference between the pretest and posttest scores of the students in the control group regarding the fairy tales they wrote, there was no significant difference between the mean of the pretest total scores (M =22.397) and the mean of the posttest scores (M =21.667) of the control group students regarding their fairy tale writing skills (p = .393, p< .05). These findings show that there was no significant difference in the total scores of the students in the control group in terms of story writing skills. Unpaired Samples t-Test was used to compare the post-test averages of the groups. The findings related to this test are given in Table 5.

Table 5. Results related to the comparison of the groups' fairy tale writing post-test scores

	Groups	N	M	Sd	t	p	d
Fairy Tale Writing Skills	Experiment	22	27.878	4.719	4.348	.002	1.15
	Control	21	21.667	5.967	4.324		

The independent samples t-test conducted to examine whether a significant difference existed between the post-test scores of the experimental and control groups in fairy tale writing revealed a notable distinction. The analysis showed that the experimental group students had a significantly higher mean total score (M =27.878) compared to the control group students (M =21.667) (p = .002, p < .05). This finding reveals that there is a significant difference in favor of the experimental group in the post-test measurements of the fairy tale writing achievements of the experimental and control groups and shows that the fairy tale writing training based on 6 + 1 traits of writing model is more effective in developing students' fairy tale writing skills than the traditional fairy tale writing training in the control group.

According to the findings in the table, while there was no significant difference between the experimental and control groups in the pre-test results regarding the total fairy tale writing scores of the experimental and control groups before the application, it is observed that the scores differed significantly in favor of the experimental group after the experimental procedure. This shows that fairy tale writing training with 6+1 traits of writing model is effective on students' fairy tale writing skills. T-Test for Related Samples was used to compare the pretest and posttest scores of the experimental group regarding writing attitudes and the findings are presented in Table 6.

Table 6. Comparison of Pre-test and Post-test Scores of the Experimental Group Regarding Writing Attitudes

	Groups	N	M	Sd	t	p	d
Writing Attitude	Experiment Pretest	22	76.18	10.28	9.390	.00054	1.87
	Experiment Posttest	22	97.95	12.89			

A paired samples t-test was performed to examine whether a significant difference exists between the pretest and posttest writing attitude scores of the experimental group students. The analysis revealed a statistically significant difference between the mean pretest score ($M = 76.18$) and the mean posttest score ($M = 97.95$) on the writing attitude scale for secondary school students ($p = .00054$, $p < .05$). According to this finding, it shows that the experimental process revealed a significant difference in terms of writing attitude in the experimental group. In this case, it can be said that the experimental group students generally improved in writing attitude after the experimental application. T Test for Related Samples was used to compare the pre-test and post-test scores of the control group regarding writing attitudes and the findings are presented in Table 7.

Table 7. Comparison of Pre-test and Post-test Scores of the Control Group Regarding Writing Attitudes

	Groups	N	M	Sd	t	p	d
Writing Attitude	Control Pretest	21	74.04	18.49	.690	.498	0.01
	Control Posttest	21	76.04	16.89			

The paired sample t-test results indicate that there is no statistically significant difference between the pre-test and post-test writing attitude scores of the control group students ($p = .498$, $p > .05$). This result reveals that the writing training in the control group didn't have a significant impact on students' writing attitude. Mann Whitney U Test, a nonparametric test, was used to compare the posttest averages of the groups. The findings related to this test are given in Table 8.

Table 8. Comparison of the Post-test Scores of the Groups Regarding the Total Scores of Writing Attitude

	Groups	N	Rank Mean	Sum of Ranks	U	p	d
Writing Attitude	Experiment	22	30.14	663.00	52.000	.00053	1.57
	Control	21	13.48	283.00			

Table 8 presents the results of the Mann-Whitney U test, which was conducted to determine whether there was a significant difference between the post-test writing attitude scores of students in the experimental and control groups. The analysis revealed no statistically significant difference between the writing attitude scores of students in the experimental group and those in the control group (p = .00053, p > .05). This finding reveals that the writing anxiety levels of the experimental and control groups don't differ from each other in a statistically significant way.

Qualitative Findings

For the third sub-question of the research, an answer was sought to the question "What are the opinions of the experimental group students about the experimental application process after the application?". The findings obtained were discussed under three themes: "cognitive characteristics", "affective characteristics" and "language and expression". Afterwards, these themes were evaluated in a holistic manner with their subcategories and codes.

Table 9. Findings Related to Cognitive Characteristics Theme

Categorie	*Code/f*	*Sample Opinion*
Knowledge (48)		
	Rule Knowledge (18)	D3 "As a positive effect of this training, it enabled me to gain more organized and rule-compliant writing skills. The negative effect is that I will spend more time to write more in accordance with the rules."
	Genre Characteristics of Fairy Tales (17)	D4 "I saw how the fairy tales I wrote became beautiful and fluent when I wrote properly, carefully and in accordance with the rules. I feel a little closer to writing fairy tales."
	Spelling Rules (7)	O1 "It was a training process that I enjoyed and it improved my fairy tale writing more."
	6+1 traits of writing model (5)	O3 "I don't know, I don't know about the issues related to the fairy tale genre."
	Narrative Forms (2)	Y4 "When 6+1 traits of writing model is mentioned, I think of the rules to be considered while writing."
	Transition and Connection Expressions (1)	Y4 "When the 6+1 traits of writing model model is mentioned, the rules to be considered while writing come to my mind."
Skill (37)		
	Writing Habit (17)	D1 "The applications affected my writing habits positively. I want to write more now."
	Writing Skill (14)	D2 "It didn't affect my writing habits much. I used to not write much, I still rarely write."
	Assesment Skill (3)	Y4 "It had a great effect. Namely, this training I received enabled me to write more beautifully."
	Enhanced Imagination (2)	O1 "It didn't contribute much to my good writing. I think it was a waste of time for us."
	Analysing Skill (1)	D2 "When I hear about the 6+1 traits of writing model, I think of writing according to the rules and evaluating the writing, identifying and improving mistakes."

Some of the codes obtained from the responses of the students were grouped under the theme of "Cognitive Characteristics" (Table 9). Under the theme of cognitive features, two categories were formed as "Knowledge" and "Skill". In the knowledge category, knowledge of rules (n=18), genre characteristics of fairy tales (n=17), spelling rules (n=7), 6+1 traits of writing model (n=5), narrative forms (n=2), transition and connection expressions (n=1); in the skill category, there are codes for writing habit (n=17), writing skill (14), evaluation skill (n=3), developed imagination (n=2), analysis skill (n=1). This finding reveals that 6+1 traits of writing model contributed to the students' knowledge of writing rules, 6+1 traits of writing model and genre knowledge about fairy tales. In addition, in the skill category, it is seen that the codes of writing habits and writing skills are predominant. It is seen that the codes of evaluation skill, developed imagination and analysis skill in this category are rarely encountered. In this context, it can be said that the 6+1 traits of writing model contributed to students' writing skills and writing habits.

Table 10. Findings Related to the Theme of Affective Characteristics

Categorie	***Code/f***	***Sample Opinion***
Attitude (45)		
	Love of Writing (21)	D1 "I had a pleasant time during the writing process. I enjoy writing now."
	Writing Anxiety (16)	O2 "Before, I didn't like writing because I had writing anxiety, now I like writing more because my anxiety has decreased."
	Self-confidence (7)	Y1 "I was worried about writing short and concise, but after I learnt that the beauty of writing doesn't depend on brevity or length thanks to this training, I no longer have such a concern."
	Boredom (1)	O3 "It makes me feel anxious, teacher."
Perception (7)		
	Waste of time (2)	O1 "It didn't contribute much to my good writing. I think it is a waste of time for us."
	Confusion (2)	D1 "The 6+1 traits of writing model reminds me of confusion. I mean, it is a complicated subject. I was a little confused after the training."
	Freedom (1)	O2 "I think that the 6+1 traits of writing model is liberation in writing."
	Modernity (1)	Y3 "My teacher gave me connotations such as thought, skill and modern writing."
	Thought (1)	Y3 "My teacher gave me connotations such as thought, skill and modern writing."
	Enjoyable Time (1)	D1 "I had a very enjoyable time during the training. Now I write with pleasure."

Some of the codes obtained from the answers given by the students to the questions in the semi-structured interview form were grouped under the theme of "Affective Characteristics" (Table 10). Some of these codes were categorized under attitude (n=45) and some under perception (n=7). In the attitude category, there are codes for love of writing (n=21), writing anxiety (n=16), self-confidence (n=7), boredom (n=1); in the perception category, there are codes for waste of time (n=2), confusion (n=2), freedom (n=1), modernity (n=1), thought (n=1), enjoyable time (n=1). According to the findings, it can be said that 6+1 traits of writing model had a positive impact on the writing attitudes of most of the students in terms of creating a love of writing, reducing/eliminating writing anxiety and gaining self-confidence, and created a positive perception in some of them. It can be interpreted that very few students formed negative perceptions towards the activities during the experimental application.

Some of the codes obtained from the answers given by the students to the questions in the semi-structured interview form were evaluated under the theme of "Language and Expression Features" (Table 11). No separate category was created under this theme. Under this theme, there are codes for fluency (n=8), conciseness (n=4), simplicity (n=4), clearness and intelligibility (n=4), persuasiveness (n=3), ornate and artistic expression (n=2), immersiveness (n=2), clarity (n=2), naturalness (n=2), sincerity (n=2), leanness (n=1). In general, students stated that the education they received made positive contributions to their language and expression features. The fact that most of the students mentioned language and expression features in their answers can be associated with the stylistic dimension of 6+1 traits of writing model and the fact that they mainly mentioned fluency can be associated with the sentence fluency dimension.

Table 11. Findings Related to the Theme of Language and Expression Features

Code/f	***Sample Opinion***
Fluency (8)	Y2 "I used to worry that my writing wouldn't be fluent and harmonious, but now I can write more fluently and harmoniously, so it has reduced my worries a lot."
Conciseness (4)	Y4 "I use concise, clear and persuasive language in my writing."
Simplicity (4)	O3 "I think I use a clear, simple and natural language, teacher."
Clearness and intelligibility (4)	Y3 "I tried to use a simple, clear, understandable and gripping language."
Persuasiveness (3)	O2 "I think I use a natural, convincing and fluent style of expression in my writings."
Ornate and artistic expression (2)	O4 "I write in a simple, entertaining, ornate and artistic style."
Immersiveness (2)	D3 "I use an ornate, artistic, gripping language."
Clarity (2)	D4 "I write clear, fluent, clear and concise. I don't think I write convincingly and plainly."
Naturalness (2)	O2 "I think I use a natural, convincing and fluent style of expression in my writings."
Sincerity (2)	D1 "I write sincerely and sincerely."
Leanness (1)	D4 "I write clearly, fluently, clearly and concisely. I think that I write convincingly and lean"

Discussion and Conclusion

This study aims to determine the effect of the 6+1 traits of the writing model on the fairy tale writing skills and writing attitudes of seventh-grade middle school students. The sample of the study, in which the exploratory sequential design, one of the mixed method designs, was composed of 43 students studying in a public school in the 2022-2023 academic year. There were 22 students in the experimental group and 21 in the control group. While the experimental group was taught story writing integrated with the 6+1 traits of the writing model, the control group was taught story writing with traditional methods. Traditional methods require a teaching process based on direct expression, based on the holistic evaluation of the product resulting from the writing activity, and in which the teacher is in a leading position. The 6+1 traits of the writing model, on the other hand, is a model that evaluates the products written by the student from many different perspectives and includes the process of the teacher giving feedback and positively guiding the student. In the study, quantitative data were collected through the 6+1 Analytical Writing and Evaluation Scale and Writing Attitude Scale for Secondary School Students within the framework of a quasi-experimental design. In contrast, qualitative data were obtained through semi-structured interviews conducted after the experimental process. The findings revealed that fairy tale writing training with the writing characteristics model significantly improved students' fairy tale writing skills and writing attitudes. Qualitative data also supported these findings and showed that students developed positive views towards the writing process. In this context, it was concluded that the 6+1 traits of the writing model characteristics model are effective in writing education processes.

The findings of this study coincide with previous research on writing instruction based on the 6+1 traits of writing. Altuner Çoban and Ateş (2022) found that this model improved pre-service teachers' writing skills and reduced their writing anxiety. Similarly, this study observed that students' attitudes toward writing changed positively, and their writing anxiety decreased. This is an important factor supporting students' more active participation in writing. In the study of Kalsum et al. (2020), it was observed that the model provided improvement, especially in the dimensions of idea development, organization, style, and spelling rules. Significant improvements in structure, organization, and style were also observed in the present study. However, no significant improvement was observed in terms of word choice and sentence fluency in the study by Kalsum et al. (2020). Although no specific evaluation was made for these dimensions in this study, significant improvements were found in general writing skills. In a quasi-experimental study conducted with third-grade students, Maynard and Young (2022) found that the feature-based teaching approach significantly increased writing achievement (d=2.38). Similarly, in this study, a significant increase was observed in the writing achievement of the experimental group in which the 6+1 traits of the writing model were applied. In this context, Rowland et al. (2020) discussed the difficulties of the 6+1 traits of the writing model in the writing processes of students with disabilities and discussed technologies that can support the development of these skills. Ramlala and Augustin (2020) found that the model, combined with blended learning and modeling techniques, helped students overcome cognitive, psychological, and linguistic barriers in the reflective writing process and improved their writing skills and positive attitudes towards writing. Furthermore, Gurusamy and Sathappan (2022) showed that the model improved the writing skills of Malaysian University students through peer assessment but also emphasized that some difficulties were encountered in the implementation process. These findings coincide with the results of the current study and reveal that the 6+1 traits of the writing model are effective in different student groups.

Within the scope of the study, the results regarding the effect of the 6+1 traits of the writing model on the writing attitudes of the students in the experimental and control groups were discussed. According to the study's findings, the post-test total mean score of the experimental group students from the writing attitude scale for secondary school students increased significantly compared to the pre-test mean score. These results show that the story writing training with the 6+1 traits of the writing model significantly benefited students' writing attitudes. In contrast, training with traditional methods could improve students' writing attitudes to a certain level. This result coincides with the findings of previous studies based on the 6+1 traits of the writing model (Görgüç, 2016; Özdemir & Özbay, 2016; Ramlala & Augustin,2020).

In quasi-experimental studies examining the effect of different teaching methods on the writing attitudes of secondary school students in Turkey, various writing attitude scales were used, and it was observed that these methods positively affected students' writing attitudes (Can & Topçuoğlu Ünal, 2019; Özdemir & Çevik, 2018; Türkben & Karaca, 2023). In Özdemir & Özbay's (2016) study, it was determined that the 6+1 traits of the writing model were effective on pre-service teachers' writing attitudes but did not create a significant difference in the spelling and punctuation sub-dimension. Görgüç (2016) found that this model positively affected sixth-grade students' writing achievement and attitudes. However, there is no study examining the effect of this model on writing attitudes in foreign literature.

In the qualitative dimension of the study, in the interviews with the students in the experimental group, it was stated that the application based on the 6+1 traits of the writing model improved their writing skills, compliance with spelling rules, and ability to write fairy tales. Most students stated that their writing anxiety decreased, and they gained a positive attitude toward writing. It was emphasized that they improved, especially in terms of fluency. These findings revealed that the model was effective in teaching fairy tale writing skills and shaping writing attitudes positively.

The 6+1 traits of the writing model aim for students to write fluent and rule-compliant texts with original ideas (Grundy, 1986; Spandel, 1997). It was observed that these qualities emerged clearly in the writings of the students in the experimental group. Post-experiment analyses showed that the model improved students' story-writing skills and that the writing process consists of interdependent components. For example, when the organization of ideas is not developed, it is insufficient to produce original thoughts (Graham & Sandmel, 2011; Seban, 2012; Gillespie & Graham, 2014). Similarly, texts containing spelling and punctuation errors reduce readability (Paquette, 2002; Werkmeister, 2010). Students may perceive The writing process as challenging, which may negatively affect their motivation to write (Colantone et al., 1998; Yaman, 2010). However, it has been observed that students' writing anxiety decreased, and their writing attitudes changed positively when they were supported with a sense of achievement and fun activities during the writing process. In this context, fairy tale writing training based on the 6+1 traits of the writing model makes significant contributions not only to cognitive skills but also to affective characteristics.

Increasing the motivation of students with negative writing attitudes and improving their writing skills is one of the main tasks of teachers (Özdemir & Özbay, 2016). When students are actively involved in the writing process with the proper methods, their writing attitudes change positively (Türkben & Karaca, 2023). The improvement in the fairy tale writing skills of the students in the experimental group can be explained by process-oriented evaluation and diversification of multisensory activities. In addition, considering the contribution of fairy tales to the development of individuals, the effect of fairy tale writing training on students' writing skills and attitudes cannot be denied. Writing education that involves, mobilizes, and motivates students increases writing success (Lane et al., 2008; Troia et al., 1999).

Limitations

The research was conducted with seventh-grade students studying in a state secondary school in Sarıyer district of Istanbul province and covers the first term of the 2022-2023 academic year. It is limited to the data obtained from the data collection tools used within the scope of the fairy tale writing training plan integrated with the 6+1 traits of the writing model. The research is limited to the opinions of the students in the group in which the fairy tale writing education plan integrated with the 6+1 traits of writing model was implemented. The research is limited to the activities implemented within the scope of the fairy tale writing education plan integrated with the 6+1 traits of the writing model.

Recommendations

The findings of this study suggest that integrating fairy tale writing instruction based on the 6+1 traits of the writing model into secondary school curricula could enhance students' writing skills and attitudes. In this context, offering fairy tale writing training as an elective course may provide students with structured opportunities to develop their narrative skills within a systematic framework. Given the significant role of fairy tales in cognitive and linguistic development, incorporating more activities related to this genre into textbooks, aligned with students' proficiency levels, could further support their writing competence. Additionally, a course specifically designed for written expression, structured around the sub-dimensions of the 6+1 traits of the writing model and enriched with targeted activities, could be beneficial in fostering students' overall writing proficiency. Furthermore, within the scope of this research, students' fairy tales were assessed using the 6+1 analytical writing and assessment scale. To enhance its applicability in secondary education, the scale could be adapted into a more simplified and comprehensible format, ensuring that students and educators can effectively utilize it in writing instruction.

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

***Ethics Statement*:** We hereby declare that research/publication ethics and citing principles have been considered in all the stages of the study. We take full responsibility for the content of the paper in case of dispute (Ethical review board name: Bursa Uludağ University Social and Human Sciences Ethics Committee, Date of ethics review decision: 03-25-2022, Ethics assessment document issue number: 2022-03-26).

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Digital Literacy, Motivation, Self-Regulation, Interest, and Task Difficulty as Predictors of Performance in Online Learning: A Path Analysis

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Abstract

Studio-based art and design education, especially in hands-on fields like ceramics, faces significant challenges during crises requiring remote learning. The sudden shift to online environments disrupts the experiential learning essential to such courses. This study examined the effectiveness of the Studio-Based Clay Course Model, which integrates multimedia tools and instructional videos to support clay instruction in both physical and virtual formats. The study investigated how digital literacy, motivation, self-regulation, course interest, and task difficulty predict academic performance in an online learning context. Data were collected via a structured questionnaire from 148 students in Ghana. Path analysis, conducted using Jamovi software, revealed that motivation, course interest, and self-regulation significantly predicted academic performance ($\beta = .6121$, $p < .001$), and task difficulty had a notable impact ($\beta = .2339$, $p = .024$). Digital literacy did not directly predict performance ($\beta = .0892$, $p = .367$) but influenced it indirectly through motivation and self-regulation. The model explained 71.4% of the variance in academic performance. While limitations such as limited digital access and challenges in replicating hands-on activities online were noted, the findings suggest that the Studio-Based Clay Course Model fosters resilience and supports student success in remote studio-based learning environments.

Keywords: Academic performance. Clay courses, Course interest, Digital literacy, Motivation, Online education, Self-regulated learning, Task difficulty.

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Introduction

The clay studio is a firmly established physical location with a distinctive teaching approach where lecturers with experience in clay-forming techniques teach students individually or in groups. This technique occasionally includes a "learning by doing" approach to instruction. The lecturer demonstrates the processes through actions, discussing, and showing clay-forming techniques. In studio-based learning, students solve problems and complete projects by thinking and acting. The clay studio is an active learning environment. During COVID-19, tertiary institutions used technology to teach and learn to prevent the spread of the virus. According to UNESCO (2020), over 1.6 billion students were affected by the pandemic at its height worldwide, which prompted a spike in the number of online learning resources and platforms to keep up with the demand. During the peak of COVID-19, online teaching and learning became the norm in educational institutions to reduce the spread of the virus, causing some students to be absent from school (Owusu-Fordjour et al., 2020). The Ministry of Education introduced an online teaching and learning platform to ensure the successful completion of the academic calendar. Studio-based clay courses in tertiary institutions relied heavily on face-to-face demonstrations to teach practice-based learning in studio environments. Most studio-based clay students in Ghanaian tertiary institutions did not attend lectures due to the lockdown implementation by the government of Ghana. They also ignored the problem of their coursework, causing poor academic performance of students. Lecturers and students hoped that technology could accompany and assist students in reviewing and preparing lessons. The lack of resilience regarding teaching studio-based practical or hands-on activities in clay courses was challenging because of the global COVID-19 pandemic. However, if there had been a resilient pedagogy, there would not have been issues teaching studio-based clay courses during the pandemic. Response to a study conducted by Adarkwah (2021) revealed that traditional teaching and learning were suitable compared to online learning, representing more than half of the study responders. Most students were unwilling to attend online lessons due to challenges such as a lack of social interactions and IT skills. They preferred traditional rather than online learning (Adarkwah, 2021). However, during the COVID-19 pandemic, the literature did not investigate how well students performed. Accordingly, the research aims to identify the factors influencing students' academic performance. Therefore, the purpose of this study is to examine the current method of teaching and learning studio-based clay courses and to present a resilient methodological pedagogic framework that could be used to incorporate the teaching and learning of studio-based practical clay courses that take into account students' motivation, course interest, digital literacy, self-regulatory learning, task difficulty and test its effectiveness with the integration of instructional technology on student's academic performance in order to ensure that tertiary students in Ghana learn effectively in times of crisis.

In architectural studios, the most widely used online teaching platforms are Zoom, Microsoft Teams, and Blackboard Collaborate Ultra (Rongrong et al., 2022). The ability for lecturers to sketch on top of students' work emulates the traditional face-to-face studio approach of sketching, making Blackboard Collaborate well-liked. No recent studies have examined the effects of traditional face-to-face versus online studio-based clay courses on students' academic performance, particularly within tertiary design education. Although flipped learning and micro-lectures are widely adopted in studio-based contexts abroad (Haritha et al., 2024; Bakir & Alsaadani, 2022), their implementation in clay instruction remains underexplored. Most tertiary students in Ghana possess smartphones, laptops, or tablets, allowing institutions and lecturers to integrate technology-enhanced learning into clay studio practice. While digital tools have improved collaboration, feedback, and creativity in design studios (Hafizah & Zairul, 2023; Fleischmann, 2022), limited research addresses their specific impact on academic performance in ceramic education. There is a critical need to investigate the factors influencing academic outcomes in online studio-based learning and to understand students' perceptions of their learning achievements. This study analyzed the factors affecting clay students' academic performance using online studio-based teaching and learning methods. The information provided is relevant to lecturers and provides valuable insights into the effectiveness of a resilient pedagogical framework for online teaching studio-based clay courses during crises. While the Studio-Based Clay Course (SB-CC) model has shown promise in enhancing academic performance, motivation, and self-regulation, challenges remain regarding digital access and the difficulty of fully replicating the hands-on nature of practical courses in an online environment.

Literature Review

Online Studio-Based Clay Course

Online studio-based clay courses involve an infusion of Information Communication Technologies (ICTs) into learning and teaching in all education sectors. Technology in education involves delivering instructional content and allowing students to observe lectures, discussions, and demonstrations in the comfort of their homes or hostels. Thanks to these technologies, lecturers can give a course synchronously and asynchronously, which creates a mobile and flexible environment. Students could study whenever and wherever they wanted to because online learning is flexible. Online studios need to provide dynamic communication between students and lecturers for clay courses to succeed during emergencies.

Mobile learning in Studio-Based Clay Course

Mobile learning is important in an educational pattern, particularly with swift technological advancements and the increasing number of mobile devices. Mobile learning has advanced from instructional materials to a flexible and easy-to-use resource, paving the way for new directions in tertiary institutions due to technological revolutions (Gizeh, 2023). The perception of mobile technologies, when developed and applied in a way that makes them appropriate for learning, has the vast potential to change the education area completely.

Along with other educational technologies, it became a sought-after tool for remote schooling during the COVID-19 epidemic, especially tablets and smartphones. The meaning emphasizes the mobility of technology, learning, and students, which is important in understanding the transformative possibility of mobile learning in various institutions (Moustaka, 2018). Even though mobile learning has been there for a while, the epidemic has made it a part of higher education. Face-to-face teaching and learning activities have had to be moved online, and lecturers must adjust to the new conditions. Due to these, lecturers and students needed specialized and effective assistance curricula. The importance of mobile learning has increased due to the widely used internet infrastructure and mobile technologies (Tolstoukhova et al., 2019). This has permitted students to participate in educational content anytime and anywhere, enabling flexible and personalized learning practices (Gong et al., 2023). Since mobile learning enables a more dynamic and student-centered approach to education, research suggests it can improve student motivation and engagement (Shahrol, 2020). Research has shown that students used their mobile devices for group projects, discussed material, and shared ideas with coursemates, improving learning outcomes and building collaborations (Gong et al., 2023). Arts-based learning approaches adapted for m-learning provide creative outlets for expression and foster essential social interactions, pivotal for successful learning outcomes (Perry & Edwards, 2019). It is important to note that mobile technology does not ensure successful learning outcomes; student preferences for learning applications often prioritize convenience over effectiveness, which may not always align with educational goals (Uther & Ylinen, 2018). By providing students with access to informative resources and chances for teamwork, mobile technologies can make online studio-based clay courses successful and promote equity of education in tertiary institutions.

Student Academic Performance

A significant component in meeting graduation requirements is the motivation and learning style of the students (Tokan, 2019). Motivation and learning behaviors such as course interest (Sun et al., 2017), digital literacy (Pala & Başıbüyük, 2023), and self-regulatory learning (Lilian et al., 2021; Zheng et al., 2024) are important factors in influencing students' academic performance. Student achievement is a measure of academic success (Gunawan, 2017). The relationship between what students expect and receive in a course can be used to determine course satisfaction. It has been demonstrated by earlier research that students engaged in their classes typically receive better marks on their final exams (Puzziferro, 2008). A substantial amount of signal indicates that course fulfillment significantly impacts academic performance. However, it can also be jeopardized due to the restricted interaction and numerous potential disturbances. The quality of the course evaluation, the relationship between students and their instructors, students' learning processes, self-efficacy, and the degree of student happiness and achievement can all be related to these elements (Owusu-Fordjour et al., 2020). Therefore, students happy with their learning experience also perform well academically, which is how studio-based clay learning can succeed.

Study Model and Hypothesis Development

The research questions were answered using students' digital literacy, motivation, course interest, self-regulatory learning, and task difficulty to test the educational goal of the student's academic performance. The variables significantly impact academic performance. This study combined motivation, course interest, digital literacy, self-regulatory learning, task difficulty, and academic performance as predictors from the literature review. Online studio-based clay teaching and learning activities are innovative and may relate to students' satisfaction and academic performance. Figure 1 shows a more complete proposed model.

Education has paid significant attention to the complex field of study on the relationship among, digital literacy, course interest, task difficulty, motivation, self-regulated learning, and academic performance. Students' involvement and interest in their courses are greatly influenced by their digital literacy, which is the capacity to use digital tools to navigate, assess, and produce knowledge successfully. Wahyuni et al. (2023) indicated a positive correlation between applying digital literacy-based learning and enhancing student motivation and social interaction skills within educational environments. The findings indicate that when students engage with digital tools effectively, their overall interest in course content and participation increases due to the interactive nature of e-learning platforms. Moreover, incorporating interactive and multimedia components into course design has significantly increased students' course interest, encouraging deeper engagement with the course (Budiarto & Jazuli, 2021).

H1: Students studying clay who are more digitally literate will be more interested in online studio-based clay courses.

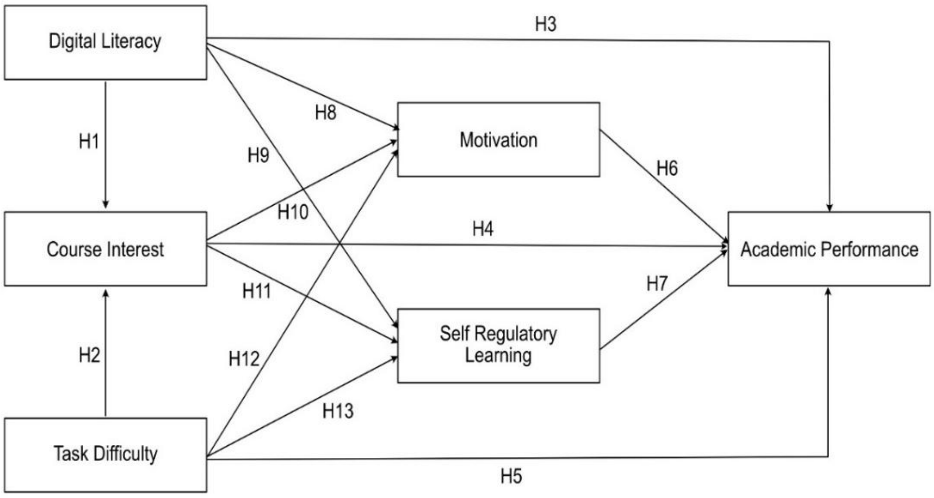

Figure 1. Research Model and Initial Hypothesis Source: Authors' Construct (2025)

Another significant component that affects course interest is task difficulty. Nuutila et al. (2021) argued that interest and self-efficacy are interlinked, suggesting that students who feel competent in engaging tasks are more likely to maintain interest even as challenge levels rise. This tendency is especially noticeable in studio settings where students are encouraged to work together and discuss the course materials, as these interactions can help challenging assignments appear more doable and pertinent (Jones, 2011). Task complexity also plays a role in shaping these perceptions. Liang (2022) indicates that task complexity can impact performance outcomes, affecting students' interest levels in learning environments. To keep students interested and engaged, lecturers must carefully balance task difficulty when assigning students to online studio-based clay courses.

H2: The perceived task difficulty in the clay studio practical has a positive impact on students' interest in the course.

Academic performance is directly impacted by digital literacy in addition to course interest. Studies have found that higher digital literacy correlates positively with improved academic outcomes, suggesting that strong digital skills are imperative for educational success in the modern age (Abbas et al., 2019). Additionally, educators' digital literacy is likewise connected to enhanced educator performance and pedagogical effectiveness, indicating that the capabilities of teachers to utilize digital resources are critical for enriching the learning environment (Wulandari et al., 2024). The theory on the significance of incorporating digital literacy instruction into academic courses to improve students' academic performance is highlighted by this relationship (Pogorskiy, 2018).

H3: Students' digital literacy in online studio-based clay courses strongly impacts their academic performance.

A significant predictor of academic performance is course interest. A student's likelihood of dedicating time and energy to their studies and attaining better results increases when they have a genuine interest in the subject matter (Luik et al., 2017). This connection is reinforced by findings showing that students who express more interest in their course naturally perform better academically because they are more driven to interact with the course materials and participate in class activities (Cortright et al., 2013).

H4: Students' interest in the online studio-based clay course positively affects their academic performance.

Moreover, a course interest can promote fundamental motivation, essential for students to remain engaged and succeed in academic settings (Milligan & Littlejohn, 2017). Students' motivation and interest to learn studio-based clay courses online using technology affect their academic performance positively. Aligning task difficulty with student capabilities enhances engagement and learning rates, reinforcing the connection between appropriate difficulty tasks and student achievement (Pavlov et al., 2021). On the other hand, if students perceive tasks as overwhelming, they may disengage, resulting in poor academic performance levels (Milligan & Littlejohn, 2016). Therefore, lecturers must consider the difficulty of tasks assigned to students to enhance their learning experiences and outcomes.

H5: Students' perceived task difficulty of the clay course work directly affects their academic performance.

Motivation can stem from various sources, including intrinsic interest in the subject matter, external rewards, and the perceived relevance of the material to students' personal and professional goals (Herpratiwi, 2022; Wang et al., 2021). Intrinsic motivation enhances students' decision-making and academic persistence (Effendi & Multahada, 2017; Hagger et al., 2005). In contrast, extrinsic motivation, such as rewards and recognition, can stimulate initial engagement but is less effective for long-term motivation (Cheng & Yeh, 2009; Wang et al., 2021). The perceived relevance of learning materials plays a critical role in motivating students, especially when they see connections to their personal goals and future careers (Vela et al., 2024; Wolgast et al., 2021). A balance of intrinsic and extrinsic motivation and relevant educational content is crucial for fostering continuous engagement and academic success (Cook & Artino, 2016; Safdari & Maftoon, 2017). Motivation is an important factor that influences entirely students' academic performance. Motivation is closely connected to self-regulated learning, as motivated students are likelier to set goals, monitor their progress, and regulate their approaches to improve their learning.

H6: Students' motivation positively impacts their academic performance in online studio-based clay courses.

Self-regulated learning, categorized by a student's capacity to succeed in his learning methods, is another significant predictor of academic performance (Miatun & Muntazhimah, 2018; Elesio, 2023). Research has established that students who employ self-regulation approaches, such as goal setting, self-monitoring, and self-reflection, tend to perform better academically (Elesio, 2023; Cicchinelli et al., 2018). This connection mostly applies to online learning environments, where students must take greater accountability for their learning due to the lack of face-to-face instruction or direct lecturer support. Suan (2023) found that while self-regulation influences achievement, it accounts for only a portion of academic performance variability, indicating that factors such as socioeconomic status and teacher quality also play crucial roles.

H7: Students' self-regulatory learning ability positively influences their academic performance in online studio-based clay courses.

The capacity to use digital platforms efficiently can empower students to take control of their learning, leading to increased self-regulation and, ultimately, better academic performance (Bakar et al., 2023; Pogorskiy et al., 2018). Moreover, digital literacy is important in enhancing motivation and self-regulated learning. Students who were skillful in using digital tools were well-equipped to participate in course materials, search for extra information, and work with coursemates, all of which increased their motivation to learn. This highlights the importance of integrating digital literacy training into educational programs to support students' motivation and self-regulatory skills.

H8: Higher digital literacy amongst clay students increases their motivation for online studio-based clay course.
H9: Students' digital literacy positively impacts their ability to self-regulate learning.

Course interest positively influences motivation and self-regulated learning (Lai et al., 2023; Prasetya, 2023). When students find a course engaging, they are more likely to be motivated to participate actively and take ownership of their learning (Albelbisi & Yusop, 2019; Barba, 2016). This fundamental motivation can lead to implementing self-regulated learning approaches, as students become more invested in their academic success. Furthermore, Trautwein et al. (2015) shows that students interested in their courses are more likely to seek additional learning opportunities and resources, further enhancing their self-regulatory capabilities. Students interested in the studio-based clay course prefer studying and taking more programs outside lecture hours to enhance their academic performance.

H10: Students' motivation is positively impacted by their interest in an online studio-based clay course.
H11: Students' interest in the online studio-based clay course has a positive impact on their ability to master self-regulatory skills.

Task difficulty also affects motivation and self-regulated learning (Jurczyk et al., 2019; Bognar et al., 2024). When students encounter challenging tasks, their motivation can either increase or decrease depending on their perceptions of the task's difficulty and their ability to succeed (Jurczyk et al., 2019). Tasks that are perceived as appropriately challenging can stimulate motivation and encourage students to employ self-regulated learning strategies to overcome obstacles (Wu et al., 2021). Students of studio-based clay courses have their practicals together, which enables them to tackle challenges together to overcome obstacles. On the contrary, if tasks are viewed as excessively difficult, students may become discouraged and disengaged, leading to lower motivation and diminished self-regulatory efforts (Villarreal-Lozano et al., 2022; Bognar et al., 2024). Consequently, lecturers must consider the difficulty of tasks assigned to students in online studio-based clay courses to not discourage learning but rather increase their learning experiences and academic performance.

H12: Students' perceived level of task difficulty with online clay-related courses has a positive impact on their motivation.
H13: Task difficulty in online clay courses has a positive effect on students' capacity for self-regulatory learning skills.

The interplay between digital literacy, task difficulty, course interest, motivation, self-regulated learning, and academic performance is complex and multifaceted. Digital literacy enhances course interest and academic performance by enabling students to engage more effectively with course materials in studio-based clay courses. Task difficulty influences course interest and academic performance by shaping students' perceptions of challenges and their motivation to succeed. Course interest, in turn, drives motivation and self-regulated learning, which are critical for academic success. Therefore, educators must consider these interrelationships when designing curricula and instructional strategies to optimize student engagement and academic performance in online studio-based clay courses. This study used intermediate variables of motivation, course interest, digital literacy, self-regulated learning, and task difficulty. Additionally, the dependent variable was Academic performance. The study proposed 13 hypotheses, presented in Figure 1.

Method

Design

Cross-sectional Correlation design was the research methodology adopted and used to construct hypotheses and analyze several attributes and outcomes simultaneously without losing track (Hackshaw, 2014; Solem, 2015). The primary focus of this approach is to examine the correlations between several constructs—digital literacy, perceived task difficulty, interest, motivation, and academic performance—serving as the analytical framework for comparing conventional and online studio-based clay education. Cross-sectional designs are frequently used in educational and psychosocial research to assess relationships among multiple factors, providing a snapshot supporting hypothesis testing and subsequent model development (Bui et al., 2021; Nurhidayah & Puspitosari, 2023). Questionnaires were distributed to students in tertiary institutions in Ghana who had taken studio-based clay courses before, during, and after the COVID-19 pandemic. This population was deliberately selected because they had experienced in-person and online delivery of clay courses, ensuring their responses' relevance and contextual validity. This methodological pattern aligns with recommendations from Spector (2019), who advocates for using cross-sectional designs with well-structured instruments to analyze correlational patterns in educational settings.

Instruments

A structured questionnaire comprising six key constructs—Academic Performance, Motivation, Self-Regulated

Learning, Task Difficulty, Course Interest, and Digital Literacy—was used to collect data, as detailed in Appendix A. All items were adapted from validated instruments in the literature and aligned with the study's conceptual framework. Academic Performance was measured using self-reported academic results. Prior studies used proxies such as task scores or game performance to assess academic outcomes (e.g., Scasserra, 2008; Lynch et al., 2013). Motivation was assessed using the Intrinsic Motivation Inventory (IMI) developed by McAuley et al. (1989) and a questionnaire adapted from Clément et al. (1994). The IMI subscales for effort/importance and perceived competence were rated on a 7-point Likert scale and are well-established regarding reliability and validity. Items reflected participants' engagement and confidence during tasks. Self-regulated learning was not directly measured in the reviewed literature but was captured through the IMI's perceived competence subscale, representing learners' confidence and self-management in learning contexts.

Task difficulty was evaluated using items from prior studies' self-reports and task manipulation techniques. For example, Scasserra (2008) used a single-item 7-point Likert scale, while Lynch et al. (2013) manipulated game speed and assessed perceived difficulty using a 5-point scale. These approaches provided both subjective and experimental perspectives on difficulty. Course interest was adapted from the Course Experience Questionnaire (CEQ), originally by Ramsden and Entwistle (1981) in the UK. Ramsden (1991) redesigned to evaluate students' perceptions at the course level, focusing on quality and accountability in higher education. The revised CEQ included 30 items across five scales: Good Teaching, Clear Goals and Standards, Appropriate Workload, Appropriate Assessment, and Emphasis on Independence. A 23-item version was later introduced, replacing "Emphasis on Independence" with "Generic Skills". Reliability was measured using Cronbach's alpha, showing moderate to high internal consistency (e.g., Good Teaching $\alpha = 0.87$). In a Malaysian study, the overall reliability was 0.80, indicating strong consistency. Responses were collected using a 5-point Likert scale, ranging from "Strongly Disagree" (1) to "Strongly Agree" (5), allowing for quantitative evaluation of students' course experiences. Digital Literacy was measured using a research questionnaire by Rafi et al. (2019), covering skills in using digital tools and online resources. The 5-point Likert scale items were expert-reviewed for clarity, though no reliability coefficients were reported.

Data Collection and Analysis

Online questionnaires were used to gather data to guarantee participant anonymity and voluntariness. Students were made aware that they were not obligated to complete the questionnaire. In the first stage, the data were entered into an Excel sheet and imported to JAMOVI version 2.3.28 for the initial analysis—a free statistical tool. A total of 148 tertiary students of studio-based clay courses completed the survey. The respondents consisted of 102 Males and 46 females, with the majority of respondents between the 21-25 age group followed closely by those between the 18 and 20 age group. A few of the students were 25 years old or older.

Regarding tertiary institutions, 98 students were the majority of respondents from Kwame Nkrumah University of Science and Technology, followed by the University of Education Winneba, which had 41 respondents. Dr. Hilla Limann Technical University had five respondents, while Takoradi Technical University had at least four. The data were analyzed using partial least squares structural equation modeling (PLS-SEM) with the assistance of Jamovi software. This method is widely used to analyze simultaneous relationships between variables and is particularly well-suited for exploratory research, where predictive accuracy and complex relationships need to be modeled effectively (Hair et al., 2019; Sarstedt et al., 2022). PLS-SEM has been shown to be effective in handling small to medium sample sizes, with studies suggesting that a sample size of 100 to 200 respondents is sufficient for reliable results in SEM studies (Hair Jr et al., 2017; Memon et al., 2021). This study's sample size of 148 is appropriate, as it falls within the range considered acceptable for conducting PLS-SEM analysis, ensuring robust estimation of the relationships between the constructs.

Results

Descriptive Statistics

When Table 1 is examined, students reported a moderate level of motivation (M = 19.0, SD = 3.90), with scores ranging from 11 to 25. The distribution was slightly negatively skewed (skewness = -0.49, SE = 0.26) and platykurtic (kurtosis = -0.49, SE = 0.51), indicating a slight left tail and a flatter-than-normal distribution. Digital literacy also had a moderate mean score (M = 18.9, SD = 3.16), ranging from 13 to 25, and showed near-normal distribution with minimal skewness (skewness = 0.05, SE = 0.26) and slight platy kurtosis (kurtosis = -0.18, SE = 0.51). Participants rated task difficulty similarly (M = 19.0, SD = 3.79), with scores ranging from 6 to 25. The distribution was moderately negatively skewed (skewness = -0.75, SE = 0.26) and slightly leptokurtic (kurtosis = 0.89, SE = 0.51), indicating a leftward tail and a more peaked distribution.

Table 1. Descriptive Statistics

					Skewness		Kurtosis	
	Mean	SD	Min	Max	Skewness	SE	Kurtosis	SE
Motivation	19.0	3.90	11	25	-.4894	.257	-.493	.508
Digital Literacy	18.9	3.16	13	25	.0541	.257	-.179	.508
Task Difficulty	19.0	3.79	6	25	-.7469	.257	.893	.508
Course Interest	16.5	4.92	5	25	-.3944	.257	-.133	.508
Self-Regulatory Learning	23.6	4.62	9	30	-.8812	.257	1.036	.508
Academic Performance	16.0	3.35	5	20	-1.0439	.257	1.556	.508

Course interest had a slightly lower mean (M = 16.5, SD = 4.92), with a range of 5 to 25. The distribution showed mild negative skew (skewness = -.39, SE = 0.26) and near-zero kurtosis (kurtosis = -.13, SE = .51), suggesting a relatively symmetrical and normal distribution. The mean for self-regulatory learning was higher (M = 23.6, SD = 4.62), with scores between 9 and 3. The distribution was negatively skewed (skewness = -.88, SE = .26) and moderately leptokurtic (kurtosis = 1.04, SE = .51), suggesting a left skew and a more peaked distribution. Finally, academic performance had a mean score of 16.0 (SD = 3.35), ranging from 5 to 2. The distribution was notably negatively skewed (skewness = -1.04, SE = .26) and leptokurtic (kurtosis = 1.56, SE = .51), indicating a concentration of higher scores and a sharper peak than the normal curve. Skewness and kurtosis values for all variables fell within an acceptable range (±2), suggesting no severe violations of normality for the purposes of parametric analysis (Kim, 2013).

Correlation Analysis

A Pearson correlation analysis was conducted to examine the relationships among students' motivation, digital literacy, task difficulty, course interest, self-regulatory learning, and academic performance in an online studio-based clay course. The coefficients obtained are given in Table 2.

Table 2. Correlation Matrix

Variable	1	2	3	4	5	6
1. Motivation	—					
2. Digital Literacy	$.68^{***}$	—				
3. Task Difficulty	$.58^{***}$	$.64^{***}$	—			
4. Course Interest	$.54^{***}$	$.50^{***}$	$.50^{***}$	—		
5. Self-Regulatory Learning	$.49^{***}$	$.42^{***}$	$.65^{***}$	$.48^{***}$	—	
6. Academic Performance	$.52^{***}$	$.51^{***}$	$.70^{***}$	$.46^{***}$	$.81^{***}$	—

$^{***}p < .001$

The results indicated statistically significant positive correlations among all variables (Table 2). Academic performance showed a strong positive correlation with self-regulatory learning ($r = .81$, $p < .001$), indicating that students who demonstrated higher self-management and learning strategies tended to achieve better academic outcomes. Task difficulty was also strongly correlated with academic performance ($r = .70$, $p < .001$), suggesting that students who perceived the course as more challenging tended to perform better, possibly due to increased engagement or effort. Moderate positive correlations were found between academic performance and both digital literacy ($r = .51$, $p < .001$) and motivation ($r = .52$, $p < .001$). These results suggest that students with higher digital skills and greater motivation were more likely to succeed in the online clay course. Course interest was positively correlated with motivation ($r = .54$, $p < .001$), self-regulatory learning ($r = .48$, $p < .001$), and academic performance ($r = .46$, $p < .001$), indicating that students who found the course engaging were also more motivated and self-directed, and tended to perform better. Task difficulty was also moderately correlated with motivation ($r = .58$, $p < .001$), digital literacy ($r = .64$, $p < .001$), and self-regulatory learning ($r = .65$, $p < .001$), showing that the perception of difficulty was linked to both internal drive and learning strategies.

Construct Validity of Measurements

The researcher employed a bootstrap of 1,000 samples to assess the stability of the estimates. This means that they used resampling methods to generate multiple datasets and then estimated the parameters for each dataset. This allows them to evaluate the reliability of the estimates and determine whether they are stable across different samples. The fit indices for the general path analysis indicate that the model fits the data well, with a non-significant chi-squared test statistic ($\chi^2 = 1.92$, p = .166), a relatively small root mean square error of approximation (RMSEA = .102), and high values for the comparative fit index (CFI = .996), Tucker-Lewis index (TLI = .949), and root mean square residual (SRMR = .017). The overall model fit was assessed with various fit indices, including the Comparative Fit Index (CFI = .996), Tucker-Lewis Index (TLI = .949), and Root Mean Square Error of Approximation (RMSEA = .102, 95% CI [.000, .323], \ (p = .212 \)), indicating an acceptable fit. The total variance explained in Academic Performance was 71%, \ (R2 = .714 \), showing that Digital Literacy, Task Difficulty, Course Interest, Self-Regulatory Learning, and Motivation collectively account for a substantial proportion of the variance in Academic Performance.

Path Analysis and Hypothesis Testing

The path analysis model illustrates the relationships among digital literacy, course interest, task difficulty, motivation, self-regulatory learning, and academic performance, as shown in Figure 2. The model demonstrates strong predictive validity with R^2 values of .309 for course interest, .525 for motivation, .448 for self-regulatory learning, and .714 for academic performance (Table 3).

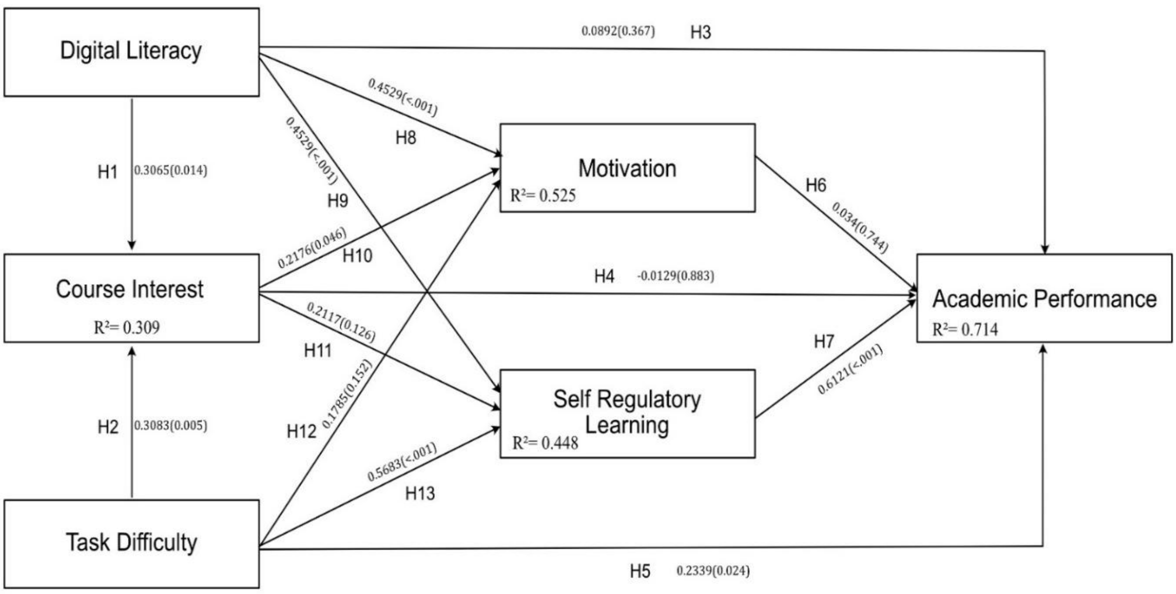

Figure 2. Path Analysis Source: Authors' Construct (2025)

Table 4 presents the parameter estimates for the tested model. Digital literacy positively impacts course interest ($\beta = .3065$, p = .014), as does task difficulty ($\beta = .3083$, p = .005), supporting the first two hypotheses. However, digital literacy does not have a significant direct effect on motivation ($\beta = .0892$, p = .367), nor does motivation directly impact academic performance ($\beta = .034$, p = .744). Self-regulatory learning, on the other hand, has a strong and significant positive effect on academic performance ($\beta = .6121$, $p < .001$), suggesting it is a critical predictor of academic outcomes.

Further relationships indicate that digital literacy significantly influences motivation ($\beta = .4529$, $p < .001$), while task difficulty also contributes to motivation (β = .2176, p = .046). Non-significant paths include task difficulty to motivation (H10), course interest to self-regulatory learning (H11), and task difficulty to self-regulatory learning (H12), highlighting that not all hypothesised paths were supported. These findings suggest that while digital literacy and task difficulty enhance course interest and motivation, their impact on academic performance is likely mediated by self-regulatory learning. Hypotheses H1, H2, H7, H8, and H9 are confirmed, whereas H3, H6, H10, H11, and H12 are not. The analysis underscores the crucial role of self-regulatory learning in driving academic performance among students.

Table 3. Explained Variance and Confidence Intervals

		95% Confidence Intervals	
Variable	R^2	Lower	Upper
Course Interest	.309	.154	.470
Self-Regulatory Learning	.448	.286	.594
Academic Performance	.714	.597	.803
Motivation	.525	.369	.658

Hypothesis 1, which posited a relationship between Digital Literacy and Course Interest, was supported with a significant estimate (β = .4767, p = .014). Similarly, Hypothesis 2, which explored the effect of Task Difficulty on Course Interest, was supported (β = .4003, p = .005). In contrast, Hypothesis 3, which examined the effect of Digital Literacy on Academic Performance, was not supported, as the p-value was .367, indicating no significant relationship. Similarly, Hypothesis 4, suggesting a relationship between Course Interest and Academic Performance, was not supported (p = .883).

Hypothesis 5, proposing a link between Task Difficulty and Academic Performance, was supported (β = .207, p = .024). The relationship between Motivation and Academic Performance in Hypothesis 6 was not supported (p = .744). On the other hand, Hypothesis 7, which examined the relationship between Self-Regulatory Learning and Academic Performance, was supported with a strong effect (β = .4436, p < .001). Hypothesis 8, proposing a positive relationship between Digital Literacy and Motivation, was also supported (β = .5584, p < .001).

Hypothesis 9, suggesting a relationship between Self-Regulatory Learning and Digital Literacy, was not supported (p = .774), while Hypothesis 10, indicating a positive effect of Course Interest on Motivation, was supported (β = .1725, p = .046). Hypothesis 11, which explored the relationship between Course Interest and Self-Regulatory Learning, was not supported (p = .126), as was Hypothesis 12, which examined the relationship between Task Difficulty and Motivation (p = .152). Finally, Hypothesis 13, which proposed a link between Task Difficulty and Self-Regulatory Learning, was supported (β = .6938, p < .001).

Table 4. Parameter Estimates

Hypothesis	Dep	Pred	Estimate	SE	95% Confidence Intervals Lower	Upper	β	Z	P	Support
H1	Course Interest	Digital Literacy	.47668	.1948	.1193	.889	.3065	2.447	.014	Supported
H2	Course Interest	Task Difficulty	.40033	.141	.1329	.666	.3083	2.839	.005	Supported
H3	Academic Performance	Digital Literacy	.0945	.1048	-.1193	.303	.0892	.902	.367	Not Supported
H4	Academic Performance	Course Interest	-.0088	.0596	-.1318	.111	-.0129	-.148	.883	Not Supported
H5	Academic Performance	Task Difficulty	.20697	.0915	.0145	.378	.2339	2.263	.024	Supported
H6	Academic Performance	Motivation	.02923	.0895	-.1405	.224	.034	.327	.744	Not Supported
H7	Academic Performance	Self-Regulatory Learning	.44358	.0696	.2942	.568	.6121	6.375	<.001	Supported
H8	Motivation	Digital Literacy	.55837	.1287	.2782	.794	.4529	4.338	<.001	Supported
H9	Self-Regulatory Learning	Digital Literacy	-.06698	.2332	-.4876	.398	-.0458	-.287	.774	Not Supported
H10	Motivation	Course Interest	.17249	.0864	.000829	.342	.2176	1.996	.046	Supported
H11	Self-Regulatory Learning	Course Interest	.19908	.1301	-.0485	.459	.2117	1.53	.126	Not Supported
H12	Motivation	Task Difficulty	.18369	.1283	-.0397	.479	.1785	1.432	.152	Not Supported
H13	Self-Regulatory Learning	Task Difficulty	.69377	.1884	.2589	.987	.5683	3.683	<.001	Supported

Discussion

The study aimed to determine the predictors related to the academic performance of studio-based clay students in tertiary institutions in Ghana. It also proposed how these factors had a relationship with academic performance. In the hypothetical model, path analysis combined Digital Literacy, Task Difficulty, Course Interest, Self-Regulatory Learning, and Motivation to account for Academic Performance. This section discusses the findings related to the study model. The effectiveness of the SB-CC model, showing the results from our path analysis, highlighted several key factors influencing student performance.

The model showed that a large portion of the variation in students' academic performance could be explained by the factors examined, with self-regulated learning emerging as the most decisive influence. This suggests that students who could manage their learning schedules, set goals, and stay focused, experienced significant academic benefits from the online learning framework. This finding supports Pintrich's (2000) self-regulation theory, as well as the work of Miatun and Muntazhimah (2018), which emphasizes that the ability to control one's cognitive and behavioral processes is crucial for academic success—especially in less structured learning environments like online courses.

Other significant predictors of academic performance included task difficulty, showing that students who perceived the tasks as appropriately challenging tended to perform better academically. This aligns with the cognitive load theory, which suggests that moderately complex tasks can enhance learning by keeping students engaged without overwhelming them (Nawaz et al., 2022). The study's analysis further revealed that motivation, digital literacy, and course interest played important roles, although not all pathways were statistically significant. For example, digital literacy did not directly affect academic performance, but it had indirect effects through other mediators such as motivation and self-regulation. These findings indicate that while digital literacy is important, other factors like motivation and self-regulation may be more critical to success in online learning environments.

The SB-CC model also positively impacted students' course interest and motivation, as evidenced by participant feedback, and aligns with the Lai et al. (2023) study. The flexibility of the online platform allowed students to revisit video content and engage with the material at their own pace, thus boosting their course interest. This is consistent with existing literature, where increased flexibility in online learning has been shown to improve student engagement and motivation. Moreover, course interest was positively associated with self-regulated learning, albeit not significantly. This suggests that while interest in the course is a factor, its direct impact on self-regulated learning may be limited (Albelbisi & Yusop, 2019; Lai et al., 2023).

Our findings on the effects of motivation also align with previous research on the impact of intrinsic and extrinsic motivation in online learning environments (Wang et al., 2021; Wolgast et al., 2021). Students in our study who were motivated to engage with the online clay course framework showed improved academic performance. This is supported by the self-regulatory theory, which maintains that intrinsic motivation, which is driven by interest or enjoyment in the task itself, plays a crucial role in academic success, especially when students have control over their learning processes.

Furthermore, our study also uncovered some challenges associated with transitioning to online learning. Technological barriers, such as access to stable internet and digital devices, were a significant issue for some students, affecting their ability to engage with the SB-CC model fully. This is a limitation also observed in similar studies by Hodges et al. (2020) and Wahyuni et al. (2023)., which highlighted the inequities caused by the digital divide, where students in less privileged circumstances face difficulties accessing online learning platforms (Alakrash & Razak, 2021). Addressing these issues is critical for ensuring that online learning is inclusive and equitable for all students.

The path analysis also identified task difficulty as a significant contributor to academic performance and motivation, aligning with the study by Pavlov et al. (2021). This reinforces the notion that when appropriately scaled, challenges can foster engagement and learning. However, when task difficulty exceeds a student's capacity, it can result in frustration and disengagement. Therefore, balancing task difficulty is essential for fostering motivation and academic success in online learning environments.

Limitation

This study has certain limitations related to staffing, scheduling, and the teaching context. The participants were drawn exclusively from tertiary institutions in Ghana offering studio-based clay courses. As such, the findings may not be generalizable to students from other universities or those studying other specializations. Future research could extend to other tertiary institutions across Ghana to validate the findings and generate more comprehensive quantitative data. The cross-sectional nature of the data limits the ability to draw causal conclusions. Future studies employing longitudinal designs are recommended to understand changes over time better. In addition, the small sample size limits the extent to which the findings can be generalized. Larger-scale studies involving broader and more varied samples would enhance the robustness and applicability of the results. Other specializations such as Painting, Sculpture, Textiles, Leatherworks, Picture Making, Bead Making, and others—could also adopt this model in different institutional settings to examine whether similar outcomes are achieved.

Conclusion

In conclusion, this study provides valuable insights into the effectiveness of a resilient pedagogical framework for online teaching of studio-based clay courses during crises. While the SB-CC model has shown promise in enhancing academic performance, motivation, and self-regulation, challenges remain regarding digital access and the difficulty of fully replicating the hands-on nature of practical courses in an online environment. Future research could explore strategies to further improve the integration of practical components into online learning, such as virtual reality tools or hybrid models that combine face-to-face and online instruction. Additionally, larger-scale studies could provide more generalizable insights and help refine the pedagogical framework to address better the diverse needs of students across different institutions and disciplines. Future research in various settings, particularly in developing nations, may benefit from the validity and dependability of the suggested model.

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

***Ethics Statement*:** We hereby declare that research and publication ethics, as well as proper citation principles, were considered at all stages of the study. Ethical approval to collect data from students was obtained from the Ethics Committee of Humanities and Social Sciences and the Department of Educational Innovations in Science and Technology at KNUST (HuSEREC/AP/33/VOL 1: 30/06/2023).

***Statement of Interest*:** We have no conflict of interest to declare.

***Data Availability Statement*:** The underlying data for this study, including participant responses and raw classroom observation data, are available on Mendeley Data (https://doi.org/10.17632/fjzy97nfwv.1).

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Appendix A

Questionnaire for Tertiary Students of Clay Courses in Ghana

This questionnaire aims to explore students' experiences with studio-based clay courses in higher education. There are no right or wrong answers; please answer honestly. Participation is voluntary, and all responses are anonymous. The survey will take approximately 10 minutes.

Section 1: Sociodemographic Information

- Age: ____________
- Gender: □ Female □ Male
- Academic Level: ____________
- Institution: ____________
- Institutional Index Number: ____________
- Cumulative Weighted Average (CWA): ____________

Section 2: Questionnaire Items

Please indicate your level of agreement with the following statements using the scale below:

1 = Strongly Disagree 2 = Disagree 3 = No Opinion 4 = Agree 5 = Strongly Agree

Motivation Factors

1. I really like learning studio-based clay courses.
2. Studying clay is necessary to me because it will enable me to produce clay works.
3. Studying clay is significant to me because I would like to make as many works as possible.
4. Studying clay is notable to me because a student is supposed to show what they have learnt.
5. Studying clay is important to me so that I can be a more knowledgeable person.
6. Studying clay is valuable to me so that I can broaden my outlook.
7. Studying clay is necessary to me because I may need it later (for job, studies).
8. Studying clay is useful to me so that I can understand clay terminologies.
9. Studying clay is meaningful to me so that I can produce clay works on my own.
10. Studying clay is important to me because I would like to become an expert.

Digital Literacy Factors

11. I know how to use digital tools to find information.
12. I am competent in using technology to collaborate and share work.
13. Instructors provide digital literacy training at the university.
14. Exposure to digital tools at university encourages continuous learning.
15. Gaps in digital skills arise when clay courses do not include applied learning with technology.

Task Difficulty Factors

16. There is a clearly defined body of knowledge to guide my work.
17. There is an understandable sequence of steps I can follow during my work.
18. I often encounter specific problems I cannot solve immediately.
19. I spend a lot of time trying to solve such specific problems.
20. In some studio practicals, things are predictable; in others, outcomes are uncertain.
21. It takes a long time before I know whether my work effort was successful.

Course Interest Factors

22. The course developed my problem-solving skills.
23. The course improved my logical skills.
24. The course helped me develop teamwork ability.
25. The course made me confident in facing unfamiliar problems.
26. The course improved my written communication skills.
27. The course helped me plan and manage my own work.

Self-Regulatory Learning Factors

28. I choose study locations to avoid distractions.
29. I choose study times with minimal distractions.
30. I take thorough notes in online courses as they are essential for learning.
31. I monitor my own learning development.
32. I seek help from knowledgeable individuals when needed.
33. I do not compromise work quality because it is online.
34. I communicate with classmates to assess my progress.
35. I communicate with classmates to compare learning experiences.
36. When I make mistakes, I adjust my behavior.
37. I plan and organize well to succeed in academic tasks (e.g., group presentations, oral work, research).
38. I summarize what I've learned in online courses to reflect on my understanding.

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Artificial Intelligence in Geography Teaching: Potentialities, Applications, and Challenges

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Abstract

This study aims to comprehensively examine the potential of artificial intelligence (AI) technologies in geography education in terms of their application domains, pedagogical contributions, and key challenges. Using a descriptive method based on a literature review, the findings reveal that natural language processing, learning analytics, location-based systems, and intelligent tutoring systems effectively support student-centered learning. AI applications contribute significantly to physical and human geography instruction mapping, classification, analysis, and prediction tasks. However, limitations such as inadequate infrastructure, disparities in teacher competencies, and ethical/privacy concerns hinder effective classroom integration. Therefore, the study recommends developing in-service teacher training programs, implementing AI-supported instructional scenarios, creating culturally responsive and localized content, and promoting ethical data use awareness. It also emphasizes the need for experimental research using quantitative and qualitative methods to evaluate AI's pedagogical value in enhancing students' mapping skills, spatial thinking, and conceptual understanding. Overall, AI technologies are not merely technical tools but transformative mechanisms capable of reshaping geography learning environments.

Keywords: Geography, Geography teaching, Artificial intelligence, Digital learning, Pedagogical transformation.

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Introduction

Geography teaching aims to help students understand the environment and global context, develop spatial reasoning skills, comprehend human-nature interaction, and gain environmental awareness. It also aims to provide students with versatile perspectives on both local and global scales and instill democratic values (Chang & Wi, 2018; Çifçi & Dikmenli, 2019; Dixit & Dixit, 2024; Lambert et al., 2015; Solem & Weiguo, 2018; Syamsunardi et al., 2024). In addition, geography teaching contributes to the development of tolerance and intercultural understanding by providing students with opportunities to interact with different cultures and geographical regions (Bustin, 2019; Dörfel et al., 2023; Honrubia-Montesinos & Otero, 2025; Kırkeser, 2021; Lambert, 2018; Miao et al., 2022; Şahin & İnce, 2021). The effective realization of these multidimensional teaching objectives in classroom environments is closely linked to the integration of technological innovations (Yılmaz, et al., 2022). Technologies such as digital cartography, remote sensing, and geographic information systems (GIS) play a critical role in enhancing students' spatial thinking skills (Arıkan, 2023; Bikar et al., 2022; Bondarenko, 2025; Hickman, 2023; Kerski, 2023; Pınar, 2017). In recent years, the inclusion of AI applications within this technological infrastructure has emerged as a promising development with the potential to significantly enhance both the effectiveness of geography teaching and student engagement.

The teaching process empowered by AI technologies, including adaptive content aligned with student performance, automated feedback mechanisms, natural language processing-oriented query-response systems, and learning analytics, has been transforming the roles of educators and students in education (Knox, 2020; Rakuasa, 2023; Ou & Chen, 2024; Zhai et al., 2021; Zhao et al., 2021). However, the integration of AI technologies into pedagogical environments has introduced several challenges, such as inadequate infrastructure, disparities in educators' technological pedagogical competences, and ethical concerns about the confidentiality of student information (Patra et al., 2024; Rakuasa, 2023; Rosenstrauch et al., 2023). Although these issues are frequently emphasised in the educational technology literature, studies specifically addressing the use of AI in teaching geography remain relatively limited. This study aims to explore the potential of using AI technologies in geography teaching, identify applicable tools and methods for use in the teaching process, determine the areas of physical and human geography where these tools may be functional, and evaluate both the opportunities these technologies offer and the limitations and risks they may present. Thus, the study seeks to contribute to the widespread and effective use of AI technologies in instructional practices by focusing specifically on their application in geography education. In this respect, the findings are considered significant for enabling teachers to develop technology-based pedagogical approaches, supporting policymakers in shaping digital education policies, and guiding researchers in producing further studies.

Artificial Intelligence in Geography: Historical Development and Its Use in Teaching

The use of AI in geography has historically evolved in parallel with the advancement of computer technologies. GIS and remote sensing technologies began to develop in the 1960s, and AI applications within these systems emerged with the development of decision support systems and expert systems in the 1980s (Couclelis, 1986). During this period, Dobson (1983) emphasized the role of computers in processing geographical data by introducing the concept of "Automated Geography." Marble and Peuquet (1983) stated that technical limitations hindered the progress of this process. Smith (1984) increased interest in AI in geography by proposing that AI can be effectively used in spatial decision-making processes. In the late 1980s and 1990s, AI technologies such as artificial neural networks (ANNs) and expert systems were experimentally applied in geographical analyses (Hewitson & Crane, 1994; Openshaw & Openshaw, 1997). Notably, Openshaw developed the "GeoComputation" approach and advocated for the more active integration of AI in geography. In the 2000s, models supported by big data, spatial statistics, and high-resolution remote sensing data came to the fore; thus, AI began to be widely applied in areas such as image processing, classification, and feature extraction. Since the 2010s, with the development of technologies such as deep learning, object recognition, route optimization, and the Internet of Things (IoT), the concept of Geographic Artificial Intelligence (GeoAI) has emerged as a significant advancement in geography (W. Li et al., 2024; Song et al., 2023). This tool has been integrated into software such as ArcGIS to support tasks such as object recognition, land cover classification, disaster management, and urban planning (Bennett, 2018; Hu et al., 2019). GeoAI has introduced new epistemological possibilities for representing and interpreting complex systems in geography.

This increasing use of AI in geographical research has been increasingly reflected in the field of education in recent years. Especially the integration of applications such as satellite image classification, spatial pattern analysis, and natural disaster modeling into teaching processes has played a crucial role in developing students' geographical skills. AI-supported software working with GIS and satellite imagery has made it possible for students to analyze phenomena such as population density, transportation routes, and urban growth on a spatial plane (Abdimanapov et al., 2025). In geographical fieldwork, deep learning algorithms and convolutional neural networks (CNNs) are widely used to visualize urbanization trends. In line with the geoscience tradition, artificial neural networks (ANNs) are used to analyze climate data, and tools such as TensorFlow support the creation of predictive water flow models based on historical climate data (Zhou, 2023). The use of these algorithms in remote sensing, water pollution modelling, soil and land classification, disaster management (e.g., earthquakes and floods), agricultural production, smart city planning, weather forecasting, and tourism geography is quite remarkable. It is also known that these applications are used in geography teaching to produce landslide susceptibility maps or to evaluate agricultural suitability based on soil classification (Rakuasa, 2023). Moreover, AI-based technologies are employed in studies that extract cultural and linguistic geographical patterns from social media data using natural language processing (NLP) tools (Wilby & Esson, 2024), as well as in geopolitical geography to identify border conflicts and energy corridors (Huang et al., 2021). This widespread use of AI technologies for pedagogical purposes in geography education, especially when combined with contemporary teaching approaches such as problem-based, project-based, and scenario-based learning, deepens the learning process and promotes an interdisciplinary perspective (Kim, 2022; Matkovič, 2024). AI transcends its role as a mere technical tool by supporting students' ability to analyze complex geographical problems and generate and communicate solutions (Rakuasa, 2023). Therefore, the integration of AI into geography education not only improves the quality of education but also prepares students for the data-driven world of the future (Zhao et al., 2021).

Literature Review

In recent years, the integration of artificial intelligence (AI) technologies into geography education has garnered increasing scholarly attention, reflecting a broader shift toward digital transformation in teaching and learning practices. Kim (2022) examined the use of AI-based tools in geography teaching. Using tools such as Teachable Machine, AutoDraw, and Deep Dream Generator, he evaluated their integration into the teaching of various geographical topics, including the classification of dune plants, the visualization of landforms, urban icon design, and the artistic interpretation of city landscapes. Almelweth (2022) investigated the effect of a teaching strategy based on AI applications on higher-order thinking skills and academic achievement in geography classes. The findings of this quasi-experimental study revealed significant improvements in favor of the experimental group, indicating that AI-supported teaching enhances both academic performance and thinking skills.

In a similar vein, Rakuasa (2023) investigated the potential of AI in geography learning and the difficulties encountered during implementation, noting that AI contributes to teaching through interactive visualization and personalized learning; however, limited access to technology, insufficient teacher training, and infrastructure inadequacies are significant barriers. Building on this technological perspective, Lee (2023) emphasized the potential of new data sources such as open data, big data, and AI in education, discussing their application in geography teaching under four main categories: geographical web services, open/big data, GIS-based fieldwork, and AI-assisted coding. Spatial inquiry activities developed within this framework are valuable tools for equipping students with 21st-century skills. Expanding the application domain to cultural and symbolic contexts, Sabato and De Pascale (2023) examined how AI influences spatial experiences, particularly in the context of video games. They emphasized the role of AI in creating virtual and symbolic spaces and its potential to offer personalised content based on individuals' geographical location. Their study provides valuable insights into how AI can offer more interactive, localized, and real-digital space-integrated gaming experiences within cultural geography.

Shifting the focus to the role of large language models, Wilby and Esson (2024) evaluated the opportunities and limitations of tools such as ChatGPT in geographical knowledge production, critical thinking, and curriculum development. They noted that the model contributes to areas such as writing support, content generation, and research evaluation; however, they also raised concerns about issues such as fabricated sources, model bias, and ethical implications. Focusing on teachers' instructional practices, Pashkova and Demianenko (2024) examined how AI technologies in geography teaching have become effective tools, especially for educators. They analyzed how neural network-based platforms such as ChatGPT, Suno, and D-ID Studio can be integrated into the production of teaching materials. These tools facilitate lesson planning, promote visual literacy and creativity, and support individualized instruction. The study also emphasized variability in teacher usage patterns and underlined the importance of training and technical support for wider adoption.

In relation to immersive learning technologies, Matkovič (2024) explored how advanced tools such as AI, virtual reality (VR), and augmented reality (AR) contribute to more engaging geography learning environments. These technologies allow students to interact with complex geographical content in sophisticated ways. Similarly, Nawaz and Sattar (2024) demonstrated that combining Geo-AI and AR in interdisciplinary earth science education leads to innovative and immersive learning experiences. Their findings highlight the role of real-world simulations in helping students understand complex spatial concepts in contextualized 3D environments.

Considering the perceptions of practitioners, Castro et al. (2025) explored elementary teachers' attitudes toward AI integration. Their findings suggest that teachers perceive AI as a tool to personalize instruction, reduce workload, and manage diverse classrooms. Importantly, they emphasize the necessity of offline-compatible tools and context-specific curricula, and advocate for robust infrastructure and professional development support. While many studies focus on opportunities, some highlight limitations. Ioanid and Andrei (2025) evaluated ChatGPT's ability to handle Romania-specific geography and history assignments. They reported frequent factual errors and geographic inaccuracies, particularly in topics with low digital representation. The study underscores the need for human oversight and the integration of localized knowledge in AI-driven instruction.

Attempting to unify these insights, Lane (2025) proposed a theoretical framework for the integration of Generative AI (GenAI) in geography education. Drawing from a wide range of literature, the framework outlines applications such as retrieval-augmented generation (RAG), environmental simulation, and spatial data visualization. Lane also critically examines implementation challenges such as hallucinations, algorithmic bias, and spatial reasoning limitations, offering a foundation for future empirical work. In a complementary study, Lee et al. (2025) adopted the SAMR model to explore GenAI's transformative potential across four dimensions of geography education: curriculum, pedagogy, assessment, and fieldwork. They not only present practical recommendations but also highlight implementation challenges that must be addressed in future research. From a regional policy perspective, Nurgazina et al. (2025) compared AI integration efforts in Kazakhstan and Uzbekistan. Based on survey data from 966 geography teachers and national documents, they found Kazakhstan more proactive in embedding AI into curricula, while Uzbekistan emphasized AI research and platform development. Both countries face shared barriers, including low digital literacy, limited access to advanced technologies, and a shortage of trained professionals. Turning to questions of equity and representation, Day and Esson (2025) provided a compelling case of how GenAI may replicate cultural bias. When asked to generate an image of students conducting fieldwork, ChatGPT produced only East Asian faces, despite no such instruction. This incident highlights the importance of critical AI literacy, particularly regarding representation and user intention in educational content.

In a practical field-based example, Liu et al. (2025) implemented an AI-enhanced course on bird habitats in China using ERNIE Bot. The tool supported students through personalized learning paths, real-time data analysis, and feedback mechanisms. Their findings suggest that AI technologies can effectively bridge theory and practice in geography education. Lastly, Alaeddinoğlu and Alaeddinoğlu (2020) explored the implications of AI for behavioral geography. They argued that processing human behavior and environmental data through appropriate AI tools could generate valuable insights, thereby providing a foundational base for future empirical investigations in this domain.

Given the literature review, it appears that AI is widely used in areas such as data analysis, mapping, and spatial modeling in the field of geography. However, the number of studies on its use in teaching processes is quite limited, and the body of knowledge in this field is still in its formative stage. In today's world, the increasing importance of geographical knowledge at both individual and social levels raises critical questions of how this knowledge is taught in a more meaningful way. In this context, this study sought answers to the following questions:

1. What is the potential of using AI technologies in geography teaching?
2. What AI tools and applications can be used in geography teaching?
3. What pedagogical opportunities do AI tools offer for geography teaching?
4. What are the limitations and possible risks associated with the use of AI tools in geography teaching?

The increasing use of AI technologies in education necessitates the redesign of teaching processes across many disciplines. However, in geography education, there is a lack of holistic and systematic research on how, to what extent, and with which pedagogical approaches AI applications can be integrated. This study aims to fill this gap by addressing the potential of using AI in geography teaching, its areas of application, as well as opportunities and limitations. The study emphasizes that AI technologies are not only digital tools but also pedagogical instruments that transform the production and transfer of geographical knowledge. Through examples presented in the context of physical and human geography, the study demonstrates how skills such as spatial thinking, data literacy, and field-based learning can be reconstructed and enhanced through AI. The study also addresses key considerations for the sustainable integration of technology by analyzing limiting factors, such as teacher competences, data security, ethical concerns, and content misalignment in the use of AI. In this regard, the study holds the potential to offer practical, critical, and forward-looking recommendations for educators, policymakers, and researchers.

Research Model

This study was structured using a descriptive research design. This approach aims to reveal the functional aspects of AI in geography teaching, offering a holistic perspective on the use of these technologies in educational settings (Rakuasa, 2023). To this end, several academic databases were utilized, including ERIC, Scopus, Web of Science, ULAKBİM, and the YÖK Thesis Database. The key terms of ‘geography education and artificial intelligence’, ‘AI in geography teaching’, and ‘AI-supported instructional methods’ were used during the search, with a particular emphasis on AI tools and applications.

The selection of studies included in the review was guided by specific inclusion criteria: (1) addressing the use of artificial intelligence technologies in geography or geography education; (2) focusing on the functionality of AI-based tools and applications within an educational context; (3) being accessible through the aforementioned academic databases; and (4) contributing to pedagogical practices, methodological innovations, or the existing body of literature. In this context, studies that merely provided general evaluations of technology without direct relevance to educational applications and those addressing artificial intelligence only indirectly were excluded from the analysis. Considering the scope and content density of the literature, a total of 76 original and recent studies were examined in detail. The findings were synthesized and reported under four thematic categories: (1) potential for use, (2) tools and areas of application, (3) pedagogical contributions, and (4) limitations and risks.

Findings

Potential of Using AI in Geography Teaching

Considering the existing literature, it can be stated that the use of AI technologies is gradually increasing; these technologies are effectively utilized in areas such as NLP, learning analytics, intelligent tutoring systems (ITS), image recognition, and location-based applications. In geography teaching, NLP technologies, intelligent chatbots, and automatic assessment systems can contribute to students' knowledge construction, written expression, and critical thinking skills (Wilby & Esson, 2024). These tools provide instant feedback by linguistically analyzing and making sense of students' written answers or questions (Bulut et al., 2024; Deeva et al., 2021; Ioanid & Andrei, 2025; Jansen et al., 2023; Parker et al., 2024). For instance, a chatbot used in geography education (e.g., ChatGPT or Socratic developed by Google) can pose open-ended questions to students, analyze their responses, and provide corrective feedback when necessary. Through the use of such AI-supported tools, pedagogical processes such as identifying conceptual misunderstandings, structuring knowledge, and promoting meaningful learning can be effectively facilitated. For example, when a student responds with a statement like, "The temperature in a region depends only on its distance from the equator" while studying the factors that influence temperature distribution, the system may recognize this as a one-dimensional line of reasoning and offer the following corrective feedback: "Temperature distribution cannot be explained solely by latitude (distance from the equator). Various geographical factors-such as landforms, continentality and proximity to the sea, elevation, air masses, and the distribution of land and sea-also play a decisive role in determining temperature."

Learning analytics is an area of AI application that guides the teaching process by analyzing large datasets derived from student interactions in digital education environments. The aim is to provide supportive, individualized learning environments for each student by identifying trends and learning needs from the data collected. Indeed, learning analytics can use online activity data to identify which subjects a student is struggling with or which types of geographical knowledge are lacking (Liu et al., 2024; Matkovič, 2024). Teachers can thus adapt the geography course content and instructional methods to better align with student needs. Prominent tools used for this purpose include KNIME, Knewton, ALEKS, Power BI (Microsoft), Moodle + Learning Analytics Plugin: Moodle LMS, ClassDojo, and Edmodo. For example, a KNIME application integrated into geography teaching can identify the stages that need revision by reporting student errors in map-reading activities. In this respect, learning analytics also provides the opportunity to design personalized learning experiences.

ITS are applications that can provide teaching materials and learning activities by adapting them to the individual needs of each student. Seterra Geography, GeoGuessr, Google Earth, Brainscape-Learn World Geography, StudyGe-World Geography Quiz, Stack the Countries, Smart Sparrow, Knewton Alta, and Century Tech are among the prominent ITS that can be used in geography teaching (Figure 1). For example, in a geography lesson unit designed to familiarise students with countries and capitals, a teacher may use different applications according to the level of each student. For beginner students, Seterra Geography can be used for country-location matching, while more advanced students can use GeoGuessr to guess random locations around the world based on visual clues. Thus, each student enhances their geographical knowledge by following a learning path tailored to their own learning pace and level. In addition, the teacher can enable students to review the capitals with flashcards through applications such as Brainscape, or have them observe the borders of continents and countries using authentic satellite images in Google Earth. Through this kind of ITS, geography lessons become both visual and interactive, and the learning process progresses in a personalised way. Research indicates that these applications enhance student motivation and have a positive impact on achievement (Ayas et al., 2015; Bahçeci & Gürol, 2010; Holmes & Tuomi, 2022).

Figure 1. ITS Examples

The most significant potential use of AI in geography teaching is image recognition and location-based applications. Image recognition applications enable land cover classification and change analysis, especially through satellite images and aerial photographs. The most common applications are Google Earth Engine and YOLO (Figure 2). For example, Google Earth Engine provides users with analysis-ready, processed data obtained from a wide range of satellites and sensors (Cao et al., 2021; Gomes et al., 2020; Gorelick et al., 2017). Similarly, object recognition algorithms such as YOLO (You Only Look Once) and Mask R-CNN are used for automatic identification of urbanization patterns, road networks, and agricultural areas, as well as real-time detection of plant species (He et al., 2020; Qiu et al., 2022; Redmon et al., 2016; Yasak, 2021).

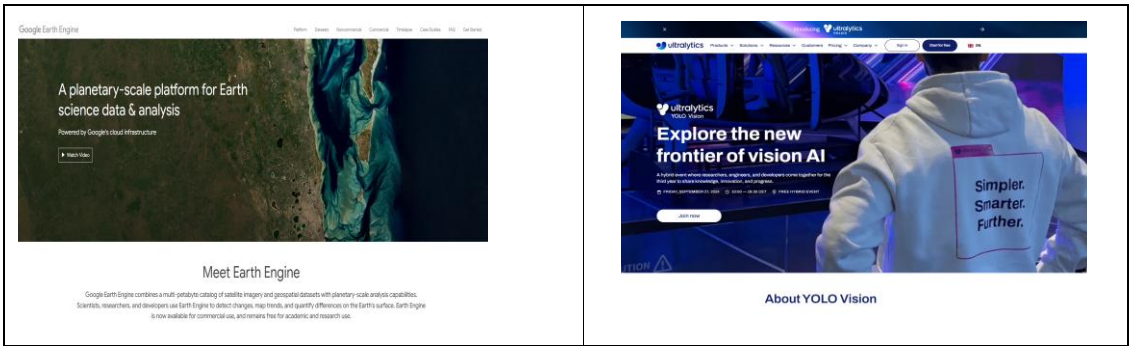

Figure 2. Examples of Image Recognition and Location-based Applications

Location-based applications allow students to collect field data directly from the environment and perform spatial analyses. In particular, GIS software such as ArcGIS and QGIS (Figure 3) enables students to analyze spatial data, create thematic maps, and engage in decision-support processes (Yıldırım & Ünlü, 2021). Applications such as Collector for ArcGIS and Survey123, which can be used on mobile devices, allow students to collect location data quickly during fieldwork; the collected data are visualised on ArcGIS Online, where density analyses are performed (Sinjari Xhafa & Kosovrasti, 2023). Additionally, digital mapping platforms such as Google Maps, OpenStreetMap, and Mapillary are utilized in classroom activities to analyze local spatial patterns and facilitate route planning (Toprak, 2023).

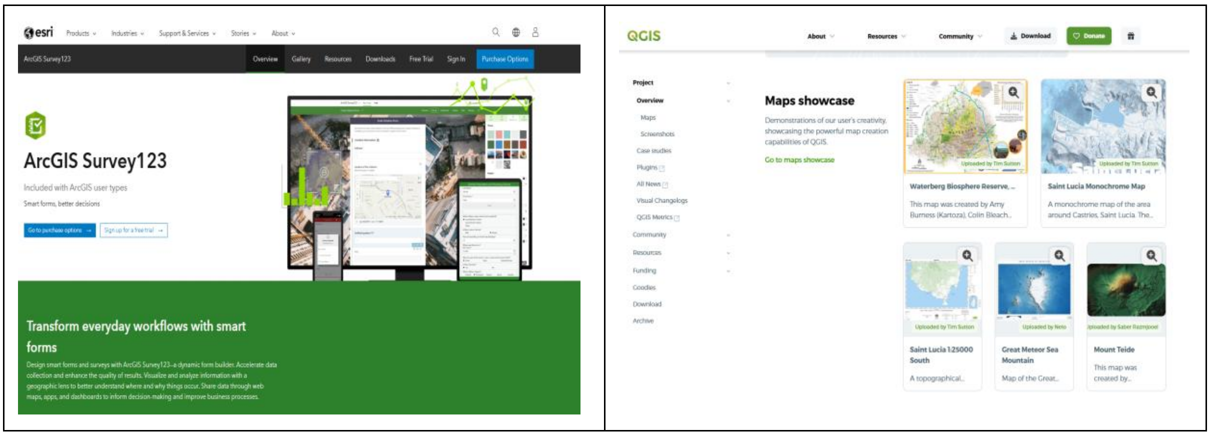

Figure 3. Examples of Location-based Applications

AR-based location applications also allow students to visualise three-dimensional landforms and compare historical maps with current data (Tuncer & Pınar, 2023; Yıldırım, 2021). With AR technology, layered information about a specific location is displayed on the student’s mobile device screen by overlaying it onto the real-world image. Thus, students can access enriched information about the geological structure, climate characteristics, or cultural elements of their environment on-site. For example, with Zappar and Metaverse Studio, a student can learn about tree species in the schoolyard through predefined content, either by seeing them on the screen in real-time or by comparing the old and new appearances of a historical place. VR and AR applications improve students’ perception of space by creating interactive and immersive learning experiences in geography education (Huang & Hu, 2025; Jantanukul, 2024; Roelofsen & Carter-White, 2022). In geography lessons, students can have the opportunity to examine real-life geographical datasets by working with AI tools that analyze drone or satellite images (Ergün, 2023). Additionally, ChatGPT-4 Geography stands out as an innovative digital assistant in geography education. This application, developed with ChatGPT infrastructure, supports students and teachers in explaining geographical concepts, developing spatial thinking, and making data-driven interpretations. GeoGebra AR and Metaverse Studio, both location-based and AR-based technologies, allow for interactive and three-dimensional exploration of topics such as landforms, climate zones, and natural disasters. For example, field-based tasks prepared with Actionbound allow students to navigate and collect data on-site, while using GeoAR.it increases spatial awareness by enabling environmental data to be presented in an AR environment.

Usage Areas and Applications of AI Tools in Geography Teaching

With the rapid advancement of digital technologies, artificial intelligence (AI) has emerged as a transformative tool in geography education, particularly in enhancing the teaching of physical geography topics. Although Pattison's (1964) concept of four fundamental geographical traditions has long been accepted among geographers, two main subfields stand out within the discipline of geography: physical geography and human geography. In the field of physical geography, it is possible to benefit from AI-based platforms in teaching topics such as landform classification, climate element analysis, river system modeling, and vegetation cover identification. Examples include studies that classify landforms using digital elevation models through Google Earth Engine (Cao et al., 2021; Safanelli et al., 2020), studies that predict temperature patterns based on climate data (Chen et al., 2023; Lewis et al., 2024; Taylor & Feng, 2022), and simulation-based models of disaster scenarios (Behravan et al., 2024; Kuratle et al., 2024; Li et al., 2024).

Moreover, AI-supported tools have become increasingly prominent in modeling and analyzing natural disaster risks within geographic contexts. The use of AI-based algorithms is growing in spatial risk analysis of natural disasters such as floods and landslides. For example, El-Haddad et al. (2021) employed AI-supported methods in spatial modeling to assess disaster susceptibility. In addition, recent studies have produced maps using algorithms such as SVM and random forest, which are among the machine learning (ML) modules of GIS. Bicák (2023) used the random forest algorithm to design an improved model for assessing agricultural drought, while Lemenkova (2024) used it to distinguish landscape patterns along the east coast of Mozambique. Additionally, Hu et al. (2019) used the same algorithm to relate the presence or absence of seagrasses to various ocean conditions.

Beyond disaster-related contexts, it is evident that AI technologies are also effectively applied in fields such as plant species classification (Adeline et al., 2021; Çulha & Ünaldı, 2025; Yasak, 2021) and the creation of fire susceptibility maps (Bayram, 2024; Iban & Aksu, 2024). It has been reported that the Diluvium Digital Elevation Model (DEM) was used to model changes in sensitive ecosystems, such as coastal areas, and environmental issues, such as sea level changes, were analyzed in detail with this model (Dusseau et al., 2023). Taken together, these studies illustrate the diverse potential of AI-based tools in supporting the teaching and learning of key topics across sub-disciplines of physical geography. Table 1 presents examples of tools and applications that can be used in various disciplinary areas of physical geography.

Table 1. Using AI in Physical Geography

Disciplinary Field	Purpose	Example Tools	Application Example
Geomorphology	Classification of Landforms	Google Earth Engine + Machine Learning (Random Forest, k-means clustering) Faster-RCNN	Students can automatically classify landforms in an area using digital elevation models. With the random forest algorithm or Faster-RCNN, forms such as mountains, valleys, and plateaus can be distinguished.

Climatology	Temperature and Precipitation Prediction	Python + Scikit-learn / Keras (Artificial Neural Network model)	Students can create an ANN model using 40 years of temperature data from a meteorological station.
Hydrography	River Flow Prediction	TensorFlow + ArcGIS Pro (Hydrology Toolbox + Python Notebook)	Students can build a model to predict river discharge based on past flow and precipitation data. Results can be analyzed with flood risk maps.
Disaster Geography	Landslide Susceptibility Analysis	ArcGIS, QGIS + SAGA GIS + SVM	Landslide risk analysis is performed in areas with steep slopes. Students can build a susceptibility model using layers such as land use, slope, lithology, and drainage density with SVM.
Soil Geography	Agricultural Suitability and Soil Classification	QGIS + SVM	Students classify suitable agricultural areas based on data such as soil type, permeability, temperature, and humidity; they identify ideal soil types for productivity using the SVM algorithm.
Biogeography	Plant Species Identification and Distribution Analysis	YOLOv5 + Drone Images + Convolutional Neural Networks + TreeSatAI	Students can classify plant species, forest cover, and endemic areas using object detection algorithms; they can perform real-time species detection.

In recent years, artificial intelligence (AI) technologies have also been increasingly utilized in the teaching of human geography, offering educators innovative ways to explore complex socio-spatial phenomena. In this context, AI-based platforms can be effectively used to analyze a wide range of topics such as urbanization processes, population mobility, migration, tourism, language, culture, education, the distribution of economic activities, and the interpretation of geopolitical risks. Convolutional Neural Network (CNN) algorithms are used in the detection and prediction of urbanization patterns (Amer et al., 2017; Fawzy, et al., 2024). Particularly, advanced deep learning models such as YOLOv5 provide effective results in the rapid analysis of targets such as building density, urban sprawl, and infrastructure monitoring using satellite and aerial imagery (Qiu et al., 2022). In population and settlement geography analyses, themes such as population distribution, urban growth, and income inequality can be interactively processed and visualized using platforms such as ArcGIS and Esri's Location Intelligence API (Chen, 2024). Furthermore, big data tools such as Google BigQuery, AutoML Tables, and Power BI allow for the large-scale analysis of migration patterns, demographic transitions, and the spatial distribution of economic activities (Huang et al., 2021).

In addition to visual and spatial data analysis, the integration of AI into human geography also includes natural language processing (NLP) technologies, which enable the interpretation of textual and cultural data. Open-source NLP tools, such as NLTK and SpaCy, can be used to analyze cultural trends and language use in a geographical context through social media data. A report prepared by the Asian Development Bank (2022) highlights the use of NLP technologies to analyze public sentiment, particularly in relation to social media discussions on COVID-19 and climate change. Such content can be visualised using tools such as GeoPandas and Tableau Public and transformed into teaching materials that can be integrated into instructional processes (Latue & Rakuasa, 2023).

Equally important, AI-based methods have been applied in tourism geography using SVM, random forest, gradient boosting trees, and GeoAI-based platforms for demand analysis, forecasting, and recommendation systems (Kırtıl & Aşkun, 2021; Kim et al., 2024). These approaches offer practical examples for planning and managing tourist destinations and help create scenario-based learning environments for geography education. In spatial network analyses—such as those focusing on accessibility and transport links—tools like ArcGIS Network Analyst, Python with NetworkX, Google OR-Tools, PGrouting, and PostGIS with PostgreSQL are frequently utilized (Geethika et al., 2025; He et al., 2024; Kostecki, 2024; Raza et al., 2024).

Finally, the use of AI-supported GIS is becoming increasingly widespread in the geographical analysis of geopolitical risks. Tools such as GeoAI Risk and Mapping ArcGIS are used to analyze the spatial distribution of hot conflict areas and geopolitical pressure zones (Baklykov, 2024). Taken together, these studies provide valuable findings on the applicability of AI-based tools in teaching subjects related to sub-disciplines of human geography. Table 2 presents examples of tools and applications that can be used in various disciplinary areas of human geography.

Table 2. Using AI in Human Geography

Disciplinary Field	Purpose	Example Tools	Application Example
Population Geography	Population Density and Migration Analysis	ArcGIS Insights, Location Intelligence API (Esri)	Students generate population density maps using location data collected from mobile devices. Supervised learning algorithms are used to classify migration patterns.
Urban Geography	Urban Development Prediction	Google Earth Engine, Convolutional Neural Networks (CNN)	Students analyze spatial urban growth using satellite imagery over time and apply CNN models to predict areas of urban expansion within the next five years.
Agricultural Geography	Land Use Identification	Drone Imagery, YOLOv5 (object detection via deep learning)	Students conduct plant health assessments based on drone imagery, identifying and classifying healthy versus unhealthy vegetation.
Tourism Geography	Destination Suitability Analysis	Weka, ArcGIS ModelBuilder	Students assess natural and cultural tourist sites based on climate, infrastructure, and accessibility, generating a suitability map for potential tourism development.
Transport Geography	Route Optimization	ArcGIS Network Analyst, Python + NetworkX, Google OR-Tools PGrouting ve PostGIS ile PostgreSQL	Students analyze public transportation systems to determine optimal routes based on traffic congestion data.

Social Geography	Spatial Analysis of Social Structures	NLTK, SpaCy GeoPandas / Shapely QGIS + Plugin'ler (ör. Orfeo Toolbox)	Students use NLP tools to analyze social media content and map the spatial distribution of variables such as language, education, and cultural practices.
Political Geography	Geopolitical Boundary and Risk Assessment	GeoAI Risk Mapping Toolkit, ArcGIS Pro, GeoPandas, Sentinel Hub	Students map geopolitical risk areas such as conflict zones and border disputes while analyzing the location of strategic energy corridors.
Economic Geography	Spatial Distribution of Economic Activities	Power BI, Google BigQuery, AutoML Tables, Orange Data Mining	Students analyze spatial data on industrial, trade, and service sectors to uncover economic patterns and regional development disparities.

Opportunities Offered by AI Technologies in Geography Teaching

The use of AI technologies in geography education not only digitizes the teaching process but also transforms the nature of learning. In this context, considering the opportunities provided by AI at pedagogical, conceptual, and practical levels, these can be listed as follows: personalised learning experiences, detection and correction of misconceptions, development of spatial thinking, data literacy and critical thinking, digitalisation of field-based learning, adaptive feedback mechanisms, and real-time interaction. To date, the use of AI in geography has been primarily concentrated in integration with GIS (Yasak, 2021). In areas such as land use classification, disaster risk analyses, spatial modelling, and image recognition, AI makes significant contributions, especially through machine learning and deep learning techniques. However, most of these applications are not directly oriented toward educational processes but are developed for geographical field research. In the context of geography education, the pedagogical potential of AI, such as personalised learning experiences, detection of misconceptions, and development of critical thinking skills, is underexplored.

AI offers adaptive learning pathways by analyzing students' individual learning needs (Baskara, 2023; Nugraheni et al., 2024; Meylani, 2024; Mulally, 2024; Pashkova & Demianenko, 2024). These platforms address students' needs by using AI to customize educational content (Mishra et al., 2024; Rakuasa, 2023; Ou & Chen, 2024). This makes it possible to create learning environments that are meaningful to the level of learning in geography courses, especially in teaching abstract concepts (e.g., landforms, climate types, and disaster susceptibility). Thanks to NLP technologies, students' open-ended responses can be analyzed semantically, and misconceptions can be detected. Systems integrated with this technology (e.g., Q-Assign and ChatGPT API) provide teachers with insights into students' meaning-making processes, allowing them to develop cognitive awareness by offering meaningful feedback to students (Balcı, 2024; Birenbaum, 2023; Ioanid & Andrei, 2025; Roldán-Álvarez, 2023).

The discipline of geography, which treats space as its central object of study, inherently involves visual, spatial, and analytical thinking. In this context, map reading and interpretation activities integrated with AI technologies such as image processing, computer vision, and machine learning significantly improve students' spatial perception and interpretation skills. In particular, tools such as Google Earth Engine, ArcGIS Image Analyst, and YOLO enable students to perform operations such as terrain classification, soil type distinction, and vegetation analysis using real satellite images, thereby directly promoting data-driven learning (Almelweth, 2022; Rana & Bhambri, 2025; Rakuasa, 2023). Thus, students' ability to analyze and interpret complex spatial problems improves. The big data processing capacity offered by AI also supports geography students in developing high-level skills, such as data literacy, pattern recognition, causal analysis, and scenario generation. AI-supported AR and location-based applications provide the opportunity to integrate with field data, regardless of physical space, in geography teaching (Shaikh, 2024). Students can collect and analyze data instantly in field studies and integrate it into digital environments. Finally, the use of AI-based applications as measurement and evaluation tools in the teaching process is also becoming increasingly widespread. These applications enable both students and teachers to monitor and evaluate their academic progress instantly. In traditional teaching approaches, measurement and evaluation processes often consume a considerable amount of time, leading to delays and a loss of motivation (Mishra et al., 2024; Ou & Chen, 2024). In this sense, AI-based assessment and evaluation tools make the learning process more interactive, motivating, and effective.

Limitations and Possible Risks of Using AI Technologies in Geography Teaching

Despite the opportunities provided by AI in teaching, there are some structural, pedagogical, and ethical limitations encountered in classroom applications. These limitations include teacher competences and pedagogical integration, inequities in infrastructure and access, ethical, security, and privacy concerns, content appropriateness and interdisciplinary constraints, a lack of empirical research, concerns about the accuracy of AI-generated information, and the risk of information pollution. In particular, teacher competences and the level of pedagogical integration appear as important limitations. Many teachers struggle to integrate AI-based tools pedagogically into classroom content, resulting in a superficial use of technology (Alasgarova & Rzayev, 2024; Meylani, 2024; Yadav, 2025). Comprehensive training programs are required for teachers to make effective use of AI tools (Arya & Verma, 2024; Tang, 2024). Research on geography teachers has revealed low levels of technology integration (Castro, et al., 2025; Lee, 2023; Matkovič, 2024; Pashkova & Demianenko, 2024; Rakuasa, 2023; Sezer et al., 2022). Notably, the lack of knowledge and methodological uncertainties about how to use AI-based applications for pedagogical purposes is also noteworthy. As a result, teachers may resort to using AI tools merely as visual aids or content delivery platforms. In this context, it is of great importance to develop applied, content-specific, and AI-oriented in-service training programs for geography teachers, as well as to design pedagogical training that is tailored to the disciplinary structure of geography.

Another fundamental limitation is inequities in infrastructure and access. Structural limitations such as inadequate infrastructure and insufficient training for educators hinder the effective integration of AI into classrooms (Zhang, 2024). This issue is particularly pronounced in rural and socioeconomically disadvantaged areas, where infrastructure deficiencies are known to exacerbate existing educational inequalities rather than promote equitable access to technology (Sasipriya & Reddy, 2024). As a result, students in these regions may face significant barriers to accessing AI-supported tools such as GIS-based map creation and analysis, online fieldwork applications, and spatial data visualization platforms. This, in turn, makes it more difficult for them to develop basic skills in geography teaching. Ethical, security, and privacy issues represent some of the most significant barriers to integrating AI in education. Particularly in AI-supported processes such as learning analytics and student behavior monitoring, the continuous collection of personal data raises various ethical concerns (Porayska-Pomsta et al., 2023; Santos, 2024; Takona, 2024). These include risks related to data security, compromised user autonomy, and a lack of transparency (Damasevicius, & Sidekerskiene, 2024; Meylani, 2024). Invasion of privacy is a serious concern, especially in student profiling systems or feedback mechanisms based on personal learning history, and can lead students to develop mistrust towards these systems (Hermansyah et al., 2023; Mustofa et al., 2025). In geography teaching, monitoring students' spatial movements, especially in applications such as location data sharing, online mapping activities, and field observations, makes these ethical risks even more visible. In addition, it is of great importance to observe ethical principles such as the protection of personal data, obtaining explicit consent, and clearly defining the purpose of data use in image recordings made during drone-assisted fieldwork and interview processes with local communities.

The direct relevance of AI applications to the teaching content also stands out as an important limitation. Wilby and Esson (2024) emphasize that ChatGPT's definition of geography does not include the basic concepts of the discipline (place, scale, space, and time), the definition put forward in the context of physical and human geography is insufficient and superficial, and AI-based applications need instructor guidance and critical thinking in terms of both content and conceptual depth. The accuracy of AI-generated information and the risk of information pollution are significant limitations, particularly in the context of chatbots (Elstad, 2024; Liu, 2024; Sidhu, 2025; Tang et al., 2023). These findings suggest that integrating AI tools directly into the educational process without critical filtering has pedagogical drawbacks. These deficiencies weaken students' ability to evaluate geographical events in a multidimensional way. Therefore, the meaningful integration of AI tools into geography education necessitates the embedding of discipline-specific conceptual frameworks within the technology. In addition, since most of these tools are English-based, language barriers and cultural context differences can also pose challenges in the teaching process (Elifas & Simuja, 2024; Kour et al., 2025; Zhang, 2024). This can result in the misrepresentation of geographical concepts, content, and cultural diversity, potentially leading to inaccurate or misleading perceptions. Therefore, the localization of AI-supported applications, provision of multilingual support, and enrichment of content with a culturally inclusive perspective are critical for meaningful, equitable, and inclusive learning experiences in geography teaching.

Although AI is increasingly becoming a topic of interest in educational research, empirical findings on its effects in teaching contexts remain limited. Chiu et al. (2023), in their systematic review of the opportunities and challenges of AI in education, state that the existing literature remains largely at the conceptual level, while empirical research on pedagogical effects is insufficient. Similarly, Zhai et al. (2021) emphasize in their systematic review of machine learning applications in education that most studies in this field are short-term and conducted with limited samples, while long-term measures of effectiveness have not yet been sufficiently developed. This situation makes it difficult to scientifically demonstrate the concrete contributions of AI to teaching processes. When considered in the context of geography education, the number of qualitative and quantitative studies that examine the effects of AI on students' geographical knowledge, map literacy, and fieldwork practices remains quite limited (Kim, 2022; Liu et al., 2025; Pashkova & Demianenko, 2024; Rakuasa, 2023). The lack of robust empirical evidence in this field presents a challenge in grounding the integration of AI into geography education on sound scientific foundations.

Discussion

This study examines the integration of AI technologies into geography teaching from a multidimensional perspective, highlighting both their potential contributions and the limitations that hinder the realization of this potential. The findings show that AI technologies have the capacity not only to digitize geography teaching but also to transform it pedagogically. However, the extent to which this transformation can be achieved depends largely on how these technologies are implemented and for what pedagogical purposes they are employed. In this sense, it is clear that AI-supported geography teaching offers not only opportunities but also structural, pedagogical, and ethical challenges that need to be addressed.

To begin with, in line with the first research question, the potential of using AI technologies in geography teaching was evaluated. The findings revealed that NLP, learning analytics, intelligent tutoring systems (ITS), and location-based applications function as tools that support student-centered learning. These technologies enable students to identify their conceptual gaps, receive instant feedback, and individualize their learning processes (Agostini & Picasso, 2024; Chang & Kidman, 2023; Wilby & Esson, 2024; Zhao et al., 2021). Thus, the learner is transformed from a passive recipient of information into an active subject who directs their own learning process. Nevertheless, for this potential to turn into genuine educational value, it is directly related to geography teachers' competences in integrating AI tools with teaching goals and their digital pedagogical formation. Considering that geography teachers' technological competencies remain limited (Nurgazina, et al., 2025; Pashkova & Demianenko, 2024; Sezer et al., 2022), it can be inferred that teachers will play a decisive role in the successful integration of AI into geography education.

In addition, within the scope of the second research question, the use of AI technologies in both physical and human geography was assessed. The findings indicated that in physical geography, AI-based classification algorithms (e.g., CNN, SVM, and random forest) can be effectively integrated into topics such as land use, soil structure, climate data analysis, and disaster risk assessment (Kim, 2022; Rakuasa, 2023; Zhou, 2023). On the other hand, in human geography, big data is transformed into valuable teaching material through location-based systems and GeoAI applications, particularly in themes like migration, urbanization, cultural geography, tourism, and geopolitical analysis (Alaeddinoğlu & Alaeddinoğlu, 2020; Castro, et al., 2025; Huang et al., 2021; Lane, 2025; Nawaz & Sattar, 2024; Sabato & De Pascale, 2023).

Despite these advancements, several challenges continue to hinder the integration of AI in real classroom contexts. These include language barriers, misalignment with curriculum content, and limited AI literacy among educators (Matkovič, 2024; Pashkova & Demianenko, 2024; Rakuasa, 2023). Nonetheless, the potential of AI technologies in geography teaching remains highly promising. Given that geography is inherently a discipline that requires multidimensional analysis to understand both natural environments and human systems, AI-based tools play a crucial role in enhancing students' ability to grasp these complex relationships.

The versatility of AI tools—such as the dual use of the YOLO algorithm in monitoring urbanization dynamics and identifying plant species—demonstrates their flexibility and applicability across diverse geography subfields.

Importantly, AI should not be viewed merely as an information delivery tool; it also serves as a dynamic learning environment that cultivates students' higher-order thinking skills such as scenario building, pattern recognition, and causal reasoning. Looking ahead, the application of AI in interdisciplinary and pressing topics—such as environmental sustainability, disaster risk management, and spatial planning—has the potential to fundamentally transform geography education, fostering more creative and holistic pedagogical approaches.

Moving forward, the third research question examined the pedagogical opportunities offered by AI technologies. The findings underscore that these technologies facilitate the implementation of contemporary instructional methods such as problem-based learning, project-based teaching, and field-based studies (Almelweth, 2022; Lee, et al.,2025; Matkovič, 2024; Nawaz & Sattar, 2024). In particular, AR applications and big data-driven visualization tools (Liu et al., 2025; Matkovič, 2024) are highly effective in enhancing students' spatial literacy and fostering meaningful interaction with their environment.

Moreover, AI-supported applications—such as image processing, computer vision, and machine learning tools (e.g., Google Earth Engine, ArcGIS Image Analyst, YOLO)—provide students with opportunities to conduct terrain classification, vegetation analysis, and soil type differentiation in a data-driven and interactive manner. This contributes directly to the development of spatial analysis and geographic interpretation skills (Almelweth, 2022; Rana & Bhambri, 2025; Rakuasa, 2023). At the same time, the big data processing capabilities of AI further nurture students' higher-order thinking skills, including pattern recognition, causal reasoning, and scenario generation.

Furthermore, in the realm of assessment and evaluation, AI-supported platforms make the learning process more flexible and measurable. Teachers can monitor student performance in real time and tailor instructional strategies based on individual differences (Lee, 2023). However, for AI technologies to produce meaningful and pedagogically sound outcomes, it is crucial that their integration aligns with geography education goals, is appropriate to student levels, and is grounded in sound instructional design. Otherwise, AI risks being reduced to a superficial trend, failing to provide real added value to learning processes.

Finally, the fourth research question explored the limitations and potential risks associated with AI technologies in geography teaching. The findings revealed several critical threats to the sustainable use of AI in education, including teachers' inadequate competencies, lack of technological infrastructure, data privacy concerns, and ethical issues (Almelweth, 2022; Hu et al., 2019; Sasipriya & Reddy, 2024). Of particular concern is the tendency of LLMs (e.g., ChatGPT) to sometimes generate inaccurate or decontextualized information, which can result in conceptual misunderstandings (Wilby & Esson, 2024).

Moreover, the lack of proper protection of student data during collection and use introduces serious ethical dilemmas and legal obligations. In addition to these concerns, language and cultural limitations of current AI tools must be acknowledged (Day & Esson, 2025; Rakuasa, 2023). The dominance of English in AI-generated content, coupled with limited representation of local cultural and geographical contexts, may cause shifts in meaning and misunderstanding—especially when teaching conceptually dense or culturally specific content (Tao et al., 2024).

Therefore, the integration of AI into educational programs should occur not only at the technological level but also at the cultural and pedagogical levels. To ensure conceptual clarity, contextual relevance, and student-centered learning, it is essential to develop localized and geography-specific AI applications. This is particularly critical in student projects involving field data—such as drone imagery or community interviews—where ethical data collection practices, including privacy protection, informed consent, and transparent use policies, are indispensable responsibilities shared by both teachers and students.

In conclusion, the lack of long-term, empirical, and discipline-specific research on the pedagogical impacts of AI in geography education (Chiu et al., 2023; Zhai et al., 2021) represents a major gap. This makes it challenging to assess AI-supported teaching practices on a strong scientific basis. The absence of such evidence hampers our understanding of how key educational goals—such as spatial reasoning, environmental awareness, and field-based inquiry—can be fostered through AI integration in geography teaching.

Conclusion

This research provides a holistic assessment of the field by examining how AI technologies can be integrated into geography teaching from pedagogical, contextual, and practical perspectives. The results show that AI applications are not only tools that digitize the teaching process, but can also create a learning ecosystem that redefines the production, transfer, and structuring of geographical knowledge. In particular, technologies such as NLP, learning analytics, location-based systems, and ITS enhance students' conceptual understanding while supporting feedback mechanisms, individualized learning pathways, and the development of higher-order thinking skills. Furthermore, the study illustrates how AI-supported tools can be applied in the context of both physical and human geography, the two major sub-disciplines of geography education. Content such as remote sensing, land use classification, and disaster modeling algorithms in physical geography, as well as urbanization patterns, migration dynamics, and spatial analysis of social media data in human geography, can be effectively integrated into the teaching process through AI-supported applications. Such applications not only facilitate the understanding of complex geographical phenomena but also promote interdisciplinary thinking and problem-solving skills among students. From this perspective, AI technologies have the potential to build a learning environment that strengthens not only students' access to knowledge but also their ability to construct, evaluate, and transfer this knowledge. This aligns with contemporary educational paradigms that emphasize active learning, student agency, and data-informed inquiry.

However, despite these promising potentials, limitations identified in the existing literature are also likely to affect geography teaching similarly. These limitations include misalignment between content and curricula, inadequate technological infrastructure, inequitable access, variations in teachers' digital pedagogical competencies, the predominantly English-based nature of AI applications, and ongoing ethical and privacy concerns. Given these challenges, this situation necessitates careful planning and implementation at pedagogical, technical, and ethical levels to ensure AI technologies' practical, inclusive, and responsible integration into geography education. Only through such a comprehensive approach can the transformative potential of AI be fully realized in supporting meaningful, context-sensitive, and equitable geography learning experiences.

Recommendations

For the successful integration of AI technologies into geography teaching, a holistic approach to using these technologies for pedagogical purposes should be adopted. This process should begin with strengthening the professional competences of geography teachers. In particular, in-service training programs should be designed to equip teachers with the skills to use AI components such as NLP, location-based analysis, and learning analytics in geography instruction in alignment with course objectives. These programs should not only focus on the technical operation of AI tools, but also emphasize pedagogical strategies for integrating them effectively into curriculum-based teaching practices.

Moreover, another important need highlighted by the findings is the development of content that supports the integration of AI-based applications into geography subjects. To address this, sample teaching scenarios involving AI use in topics such as disaster management, soil classification, urban growth, migration, and geopolitical analysis should be created. These scenarios should be tested through pilot applications at different educational levels. In this regard, collaboration between academics, curriculum developers, and practicing teachers is particularly valuable for ensuring the relevance and feasibility of AI-integrated instructional designs.

In parallel with these developments, it is essential to conduct experimental studies using both quantitative and qualitative research methods to evaluate whether AI technologies contribute pedagogically to geography education. These studies could examine the impact of AI applications on students' map-reading abilities, spatial thinking, and conceptual understanding, thus providing evidence-based insights into the effectiveness of such technologies in real classroom settings.

In addition to pedagogical considerations, preventive measures should be taken to address the limitations of AI technologies. Challenges such as the predominance of English-language content, the underrepresentation of local contexts, and cultural mismatches may cause misconceptions or alienation in geography lessons. Therefore, it is imperative to develop localized, multilingual, and culturally responsive content that can be meaningfully integrated into national curricula.

Equally important is the need to ensure that the use of AI-based applications in educational environments is conducted in a safe, transparent, and ethical manner, with particular attention to the protection of personal data. This is especially crucial in learning analytics, location-based services, and profiling-based feedback systems that involve student data processing. Policies must be developed based on transparent data usage, informed consent, and respect for user autonomy. Additionally, students should be trained in ethical data collection practices—such as securing legal permissions and protecting privacy—particularly when engaging with tools like digital mapping, field observations, or drone technologies.

Finally, structural barriers such as inadequate technological infrastructure and digital inequality must be addressed. Limited access to hardware, software, and internet connectivity—particularly in rural or socioeconomically disadvantaged areas—can prevent equitable participation in AI-enhanced geography education. Therefore, educational policies should prioritize expanding access to technological resources to ensure that all students benefit equally from the pedagogical opportunities AI can offer.

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

***Ethics Statement*:** We hereby declare that research/publication ethics and citing principles have been considered in all the stages of the study. We take full responsibility for the content of the paper in case of dispute. This study does not involve qualitative or quantitative data collection methods that require ethics committee approval, such as surveys, interviews, focus groups, observations, experiments, or similar techniques. Therefore, obtaining approval from an ethics committee does not apply to this research.

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How Technological Readiness Shapes Pre-Service Teachers' Digital Material Design Competencies: A Structural Equation Modeling Approach

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Abstract

Despite the growing emphasis on digital competencies in teacher education, many pre-service teachers struggle to design digital learning materials effectively. Among the influencing factors, technological readiness, defined as individuals' tendency to adopt and embrace new technologies, has emerged as a critical but underexplored predictor. This study investigates how technological readiness impacts digital material design competencies among pre-service teachers while also exploring the roles of gender and personal computer ownership. Drawing on data from 506 education students at a Turkish university, this study employed the Technological Readiness Scale and the Digital Material Design Competencies Scale. Structural equation modeling (SEM) confirmed that technological readiness significantly predicts digital material design competencies, highlighting the centrality of affective and cognitive preparedness over demographic or access-related variables. When gender, computer ownership, and grade level were controlled, technological readiness was found to be a significant predictor ($\beta = .63$, $p < .001$). These findings emphasize that fostering technological optimism and innovativeness may be more effective in enhancing digital competencies than focusing solely on access or demographic equity. The study suggests that teacher education programs should embed readiness-building interventions early in training to better equip pre-service teachers for technology-integrated classrooms.

Keywords: Digital competencies, Digital material design competencies, Educational technology, Pre-service teachers, Structural equation modeling, Technological readiness.

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Introduction

As education systems worldwide respond to rapid technological advancement, the digital preparedness of teachers has become a fundamental concern. In this evolving context, the ability to create and integrate digital learning materials has emerged as a key professional competency. Modern teacher education programs must therefore go beyond promoting basic digital literacy. They are increasingly called upon to prepare teachers who can design instructional materials, select and implement appropriate technologies, and evaluate their pedagogical impact (Redecker, 2017). These growing expectations place digital material design competence at the core of teacher preparation efforts.

Despite this emphasis, numerous studies continue to report that many pre-service teachers assess their digital competencies as modest or incomplete (Tatlı & Akbulut, 2017; Bediroğlu, 2021). While access to training and infrastructure certainly contributes to this issue, recent research suggests that psychological and affective factors also play a significant role in shaping digital competency development (Redecker, 2018; Muehlburger et al., 2022). One such factor is technological readiness, defined as an individual's general attitude and emotional orientation toward using new technologies. Rather than being a simple measure of experience or confidence, technological readiness comprises both encouraging and discouraging tendencies that jointly influence how people relate to digital tools (Parasuraman, 2000; Parasuraman & Colby, 2001; Rodríguez et al., 2024). This framework offers a valuable lens for understanding how teacher candidates either embrace or resist opportunities for digital learning and creation.

Within this framework, specific psychological traits such as optimism, innovativeness, discomfort, and insecurity are particularly relevant. Optimism is associated with positive beliefs about the benefits of technology, which can lead to more enthusiastic and experimental uses of digital tools in instruction (Blayone, 2018). Innovativeness supports risk-taking and a willingness to explore new tools, which are crucial for developing advanced digital design skills (Álvarez-Marín et al., 2023). Conversely, discomfort and insecurity often lead to avoidance behaviors and limited engagement with technology-rich tasks, thereby constraining the depth of digital integration (Pozas et al., 2022). These psychological tendencies are widely viewed as foundational to technology adoption and professional growth, suggesting they may significantly influence how pre-service teachers build instructional competencies.

Research Gaps and Context

However, while these theoretical associations are well established, the empirical relationship between technological readiness and digital material design competence among pre-service teachers remains underexplored. Most prior studies have either focused on in-service teachers or assessed general digital skills, neglecting this specific population. For example, Polat et al. (2022) highlight that e-learning readiness studies typically target K–12 or higher education teachers, with few examining other teacher levels. Similarly, Rafiq et al. (2022) point out a notable gap in research addressing whether pre-service teachers are ready to teach online, despite the abundance of TPACK-related studies.

In the Turkish context, only a handful of studies have touched on adjacent issues. Kabaran and Altan (2022) explored Turkish teacher candidates' reflections on digital material design, while Kaçar (2022) studied Turkish EFL pre-service teachers designing digital materials within the TPACK framework. Ata and Yıldırım (2019) used factor analysis and ANOVA to examine how attitudes and technical, cognitive, and social skills predicted Turkish pre-service teachers' self-reported digital literacy. Yet, none of these studies incorporated technological readiness as a predictor or employed multivariate modeling techniques to assess its relationship to digital design competence.

Moreover, demographic and contextual variables such as gender, grade level, and access to personal computers have been examined in isolation but rarely controlled for within an integrated analytical model. For instance, Demirtaş and Mumcu (2021) found that ICT and TPACK scores were higher among students in later years of study and those owning a personal computer, though gender showed no significant effect. Cuhadar (2018) reported differences in digital readiness based on gender and department, and Grande-de-Prado et al. (2020) observed that male trainees tended to rate their ICT skills higher than females. These findings suggest that variables such as year of study, computer access, and gender may influence digital competencies, yet their combined effects within a predictive framework remain underexamined. Structural Equation Modeling (SEM) offers a powerful methodological approach to address this gap. Though SEM has been used in related domains—for example, Chu et al. (2023) modeled Chinese pre-service teachers' digital teaching competence, and Falebita and Kok (2025) demonstrated that technological readiness predicts AI adoption—no existing study has used SEM to test whether technological readiness predicts digital material design competence in pre-service teachers while simultaneously controlling for relevant demographic variables.

Technological Readiness: A Multidimensional Framework

To understand how psychological factors, influence digital competency development, it is essential to examine the concept of technological readiness in depth. Technological readiness (TR), broadly defined as an individual's propensity to embrace, adopt, and effectively use new technologies, originates in Parasuraman's (2000) model. This model comprises four core psychological traits influencing openness to technology: optimism (a positive belief that technology offers benefits and improves productivity, enhancing learning and work environments), innovativeness (a tendency to seek out and try new technologies before others), discomfort (anxiety or a perceived lack of control over technology), and insecurity (doubts about technology's reliable functioning or trustworthiness in professional settings) (Parasuraman, 2000; Muehlburger et al., 2022). Within this framework, optimism and innovativeness act as adoption drivers, associated with curiosity, adaptability, and confidence, while discomfort and insecurity serve as inhibitors (Parasuraman, 2000).

In teacher education contexts, TR extends beyond these psychological attitudes to encompass technical competence, pedagogical adaptability, and psychological comfort (Aditya, 2021). Aditya (2021) defines a teacher's TR largely in terms of "the teacher's ability of utilizing technological software and hardware and the extent of their comfort to use it to facilitate teaching." Practically, TR is viewed as a multifaceted readiness for technology-enhanced teaching, integrating technological (knowledge of devices/tools), pedagogical (ability to adapt teaching methods), and psychological (motivation/attitudes) components, where deficits in one dimension can negatively impact others (Aditya, 2021).

The psychological components of TR have particularly strong implications for instructional design activities. Teacher candidates high in optimism are more likely to perceive digital tools as beneficial for classroom practice and explore their use in instructional design (Blayone, 2018). Similarly, an innovative mindset supports valuable experimentation and independent exploration for building technical skills and adapting resources (Álvarez-Marín et al., 2023). Conversely, high discomfort may inhibit engagement with basic software, and insecurity may lead to avoidance or minimal effort in technology-based tasks (Pozas et al., 2022). These psychological traits shape not only adoption but also the depth of skill development for effective classroom integration (Blayone, 2018; Pozas et al., 2022).

Empirical studies underscore TR's critical role in educational contexts. The Technology Readiness Index (TRI), adapted for educators, has been used to measure public school teachers' readiness, identifying segments like "explorers" and "laggards" and confirming the scale's cross-cultural validity (Badri et al., 2014). Crucially, during crises like the COVID-19 pandemic, TR proved pivotal: teachers with higher readiness (blending confidence, competence, and positive attitudes) experienced less stress, fewer disruptions, and greater success in adapting to emergency remote teaching (Pozas et al., 2022; Van der Spoel et al., 2020, cited in Pozas et al., 2022). Van der Spoel et al. (2020) argue TR is a "key professionalization factor" for successful EdTech integration. Conversely, low TR correlated with anxiety, burnout, and ineffective tech integration, hindering adoption and negatively impacting well-being (Pozas et al., 2022).

Despite TR's established importance, significant gaps persist in understanding its relationship to complex pedagogical tasks. Relatively few studies examine how specific TR components influence complex pedagogical tasks like designing educational content or evaluating learning materials (Blayone, 2018). Furthermore, antecedents beyond the core traits, such as prior ICT experience, self-efficacy, training, generational differences, contextual factors (e.g., infrastructure, support), and social-psychological dimensions like managing techno-stress, also shape teacher readiness and interact with its dimensions (Kim et al., 2019; Pozas et al., 2022). For instance, Pozas et al. (2022) found prior ICT experience strongly predicted readiness and coping during COVID-19. This highlights TR's multifaceted nature, where successful technology integration requires synergistic development across technical, pedagogical, and psychological domains, yet the mechanisms through which readiness influences skill acquisition beyond surface-level engagement remain unclear.

Digital Material Design Competency: Beyond Basic Technology Use

While technological readiness provides the psychological foundation for technology adoption, the practical application of these dispositions manifests through specific competencies. Digital material design competency represents teachers' ability to create effective digital instructional materials (multimedia lessons, interactive resources) that enhance learning. This competency extends far beyond basic technology use to encompass pedagogical integration, creativity, and evaluation (Göçen Kabaran & Uşun, 2021). This requires blending technological proficiency with pedagogical design: teachers must operate tools while contextualizing content to align with learning objectives.

Göçen Kabaran and Uşun (2021) operationalize this competency through four critical subdimensions. Designing and Developing encompasses creating original materials, Technical Competence involves using tools and software effectively, Techno-Pedagogical Competence requires integrating pedagogy with technology, and Application and Evaluation focuses on implementing and assessing impact. Each subdimension demands different combinations of technical skills, pedagogical knowledge, and creative thinking. Research reveals that these competencies are indeed multifaceted and challenging to develop. Teachers strong in innovative pedagogy show higher digital design skills (Kuloğlu, 2022), and pre-service teachers can develop "multifaceted digital capacities"—including designing digitally-enhanced materials—through targeted training (Kabaran & Altan, 2022). However, studies reveal significant gaps: while some pre-service teachers report moderate-to-high competency (Kadioglu & Ozkay, 2022), many lack confidence in aligning digital content with instructional goals or addressing learners' individual needs (Bediroğlu, 2021; Kuloğlu, 2022). This pattern suggests that effective design demands not only technical skills but also reflective thinking, decision-making, and technological fluency—capabilities that are unlikely to develop without positive internal dispositions toward technology (Bediroğlu, 2021).

Bridging Psychological Readiness and Design Competency

Given the complexity of both technological readiness and digital material design competency, understanding their relationship becomes crucial for teacher education. Although there is theoretical alignment between these constructs, very few studies have examined them in relation to each other. Most existing research focuses either on general digital literacy or on surface-level digital skills, leaving little known about how specific readiness traits support or inhibit the development of individual competencies involved in instructional design (Blayone, 2018; Pozas et al., 2022).

The theoretical connections suggest targeted relationships between specific readiness components and design competencies. For example, optimism may support the confidence needed to engage in the creative aspects of lesson planning and content development, while discomfort could limit the willingness to explore complex features of design platforms (Muehlburger et al., 2022). Innovativeness may encourage experimentation with advanced tools and multimedia applications, whereas insecurity might discourage the evaluation and revision of digital materials (Álvarez-Marín et al., 2023). These patterns suggest that the components of technological readiness may have differentiated effects on particular aspects of digital competence, yet these potential relationships remain largely theoretical.

Three key implications emerge from this theoretical framework. First, psychological foundations reveal that TR's drivers (optimism, innovativeness) may enable the risk-taking and persistence needed for complex digital design tasks, while its inhibitors (discomfort, insecurity) could hinder the reflective practice required for techno-pedagogical competence. Second, a potential skill development loop may exist where pre-service teachers with higher technology acceptance demonstrate stronger digital design competency (Kadioglu & Ozkay, 2022), and conversely, training in digital design may boost TR components like confidence (Kabaran & Altan, 2022). Third, training imperatives suggest that without explicit attention to both psychological readiness and technical competency, teachers may continue to show low digital competence (Domínguez-González et al., 2025), necessitating programs that integrate technical skill development (Aditya, 2021), guided practice in pedagogical design (Göçen Kabaran & Uşun, 2021), and cultivation of psychological readiness (Kim et al., 2019). However, most studies in this area treat readiness and competence as uniform characteristics rather than complex constructs composed of distinct but interacting traits. As a result, research has not yet clarified which dispositions are most closely related to specific skills, nor how teacher education programs might address these relationships in their training models. Furthermore, most existing research relies on correlational or regression methods, rarely employing multivariate approaches like Structural Equation Modeling (SEM) that can account for latent variables and control for confounding factors.

Purpose and Hypothesis of the Current Study

This study addresses the identified gaps by empirically examining how technological readiness predicts digital material design competencies among Turkish pre-service teachers. Despite growing recognition of both constructs, research has yet to examine their relationship in this population. Most prior studies have treated them separately—for example, profiling teachers' readiness for technology integration (Cuhadar, 2018; Polat et al., 2022) or assessing their digital content creation skills (Göçen Kabaran & Uşun, 2021; Şimşek & Yazıcı, 2021)—but the link between a teacher's tech-readiness mindset and their ability to design digital materials remains unexplored. This gap is notable because theory suggests the two may be interconnected: a teacher unready to adopt new technology might also be hesitant or less effective in designing digital resources.

The study aims to contribute both theoretically and practically. Theoretically, it integrates two strands of teacher education research—technology adoption (tech readiness) and digital instructional design—offering a more holistic understanding of teacher preparedness in the digital era. Practically, it will inform teacher education: if technological readiness strongly influences digital design skill, then programs should embed strategies to boost readiness (e.g., building confidence with tech) alongside hands-on design training. Ultimately, this study seeks to help teacher educators prioritize and align their curricula so that pre-service teachers not only can use technology, but are also ready to harness it creatively in lesson design, closing the gap between tech potential and classroom practice.

To fully understand this relationship, it is also necessary to account for key contextual and demographic factors that may influence digital competency development. Variables such as gender, grade level, and personal computer ownership have been shown to affect technology-related outcomes in prior studies, though their roles often diminish when attitudinal factors like readiness are taken into account. Therefore, this study examines whether the predictive relationship between technological readiness and digital material design competencies holds when these variables are statistically controlled.

Based on the theoretical framework and existing literature, the following hypothesis is proposed: When gender, grade level, and personal computer ownership are controlled for, technological readiness will significantly and positively predict pre-service teachers' digital material design competencies.

Method

Research Design

This study employed a quantitative, cross-sectional design to investigate the predictive relationship between technological readiness and digital material design competencies among pre-service teachers. This design was selected as appropriate for examining complex variable interactions and establishing predictive relationships in educational technology research (Creswell & Creswell, 2023; Kline, 2016). Structural equation modeling (SEM) was utilized as the primary analytical approach to test the hypothesized model, enabling simultaneous assessment of multiple relationships among attitudinal, demographic, and contextual factors.

Participants

A convenience sample of 506 pre-service teachers from the Faculty of Education at Eskişehir Osmangazi University, Türkiye, participated in the study. The sample size was determined to exceed the minimum requirements for SEM analysis, following recommendations of at least 10 participants per parameter estimated (Kline, 2016). Participants' ages ranged from 18 to 25 years (M = 21.3, SD = 1.8), which is representative of the typical age range of undergraduate education students in Türkiye. Complete demographic characteristics of the sample are presented in Table 1.

Table 1. Participant Distribution by Demographic Characteristics

Variable	Group	N	Percentage
Gender	Female	384	75,9
	Male	122	24,1
Class level	1	144	28,4
	2	169	33,4
	3	55	10,9
	4	138	27,3
Personal Computer Ownership	Yes	373	73,7
	No	133	26,3
	Total	506	100,0

Instruments

To measure the constructs of interest, two validated scales were employed, selected for their established psychometric properties and relevance to the study's objectives. The Technological Readiness Scale and the Digital Material Design Competencies Scale were used to assess participants' technology adoption tendencies and digital material design skills, respectively. Both scales have been widely applied in educational technology research and have demonstrated validity in the Turkish context (Esen, 2011; Göçen Kabaran & Uşun, 2021).

Technological Readiness Scale (TRS)

Originally developed by Parasuraman (2000) and adapted for Turkish contexts by Esen (2011), the TRS measures individuals' propensity to adopt and use new technologies. The 36-item scale encompasses four sub-dimensions: Optimism (12 items; e.g., "Technology gives me more freedom"), Innovativeness (8 items; e.g., "I enjoy experimenting with new devices"), Discomfort (8 items; e.g., "I avoid technology that requires troubleshooting"), and Insecurity (8 items; e.g., "I don't trust automated systems"). Responses are recorded on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). In this study, the TRS demonstrated strong internal consistency ($\alpha = 0.89$ overall), with subscale reliabilities ranging from 0.79 (Discomfort) to 0.85 (Optimism), which is consistent with prior validations ($\alpha = 0.88$–0.94).

Digital Material Design Competencies Scale (DMDCS)

Developed by Göçen Kabaran and Uşun (2021) specifically for pre-service teachers, the DMDCS assesses abilities to create pedagogical digital materials. The 31-item scale comprises four subscales: Design/Development (10 items; e.g., "I can align multimedia content with learning objectives"), Technical Skills (8 items; e.g., "I can edit video clips for lessons"), Techno-pedagogical Integration (7 items; e.g., "I adapt materials for diverse learners"), and Implementation/Evaluation (6 items; e.g., "I assess digital materials' effectiveness"). All items are rated on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The scale showed excellent reliability in this study ($\alpha = 0.92$ overall), with subscale reliabilities ranging from 0.81 (Implementation) to 0.88 (Design), closely aligning with the developers' original reports ($\alpha = 0.91$).

Data Collection Procedures

Data were collected during the spring semester of 2023 using an electronic survey administered via Google Forms. Participants received a standardized invitation through their institutional email addresses, which included the study's purpose, confidentiality assurances, and a direct link to the survey. Prior to survey completion, participants read and provided informed consent electronically. No financial or academic incentives were offered to minimize coercion risks, adhering to ethical guidelines for voluntary participation (APA, 2020). The survey remained accessible for four weeks, with follow-up reminder emails sent at weekly intervals (7, 14, and 21 days) to enhance response rates. The final dataset was cleaned and prepared for analysis following standard procedures for missing data assessment and outlier detection.

Statistical Analysis

Data analysis was conducted using IBM AMOS (version 25.0) to examine the relationships between technological readiness, digital material design competencies, and demographic variables. The analysis followed a multi-step approach to ensure robust model testing. Initially, descriptive statistics (means, standard deviations, and frequency distributions) were computed to characterize the sample. Data screening procedures were implemented to assess data quality and assumptions. Outliers were assessed using Cook's distance values, with no values exceeding 1, indicating the absence of multivariate outliers in the dataset (Yurt, 2023). Subsequently, skewness and kurtosis values were calculated; all fell within the ±1 range, confirming that the normality assumption was met (Hair et al., 1995). Multicollinearity was evaluated using variance inflation factor (VIF) values, all of which were below 3, indicating no multicollinearity issues (Yurt, 2023). Bivariate analysis was conducted using Pearson correlation coefficients to assess linear associations between continuous variables prior to the main analysis. Structural equation modeling (SEM) was then employed as the primary multivariate analysis to test the hypothesized predictive relationships. In the SEM model, technological readiness was specified as an exogenous latent variable, digital material design competencies as the endogenous variable, and gender, class level, and personal computer ownership as observed covariates. Model fit was evaluated using multiple goodness-of-fit indices (χ^2, RMSEA, CFI, SRMR, TLI, and IFI), following Hu and Bentler's (1999) recommendations for robust SEM evaluation.

Results

Correlation Analysis Results

Table 3 shows the correlations between demographic variables (grade, gender, computer ownership), technological readiness factors (optimism, innovativeness, discomfort, insecurity), and digital material design competencies (design and development, technical skills, technological pedagogical competence, and implementation and evaluation competence). Significant positive correlations were found between optimism and all dimensions of technological competencies: design and development ($r = .31$, $p < .01$), technical skills ($r = .36$, $p < .01$), technological pedagogical competence ($r = .27$, $p < .01$), and implementation and evaluation competence ($r = .30$, $p < .01$). Similarly, innovativeness was strongly and positively associated with design and development ($r = .47$, $p < .01$), technical skills ($r = .48$, $p < .01$), and moderately with other dimensions. In contrast, discomfort and insecurity were negatively correlated with technological competencies. The discomfort was negatively related to design and development ($r = -.13$, $p < .01$) and technical skills ($r = -.16$, $p < .01$), while insecurity was negatively associated with design and development ($r = -.15$, $p < .01$) and technical skills ($r = -.13$, $p < .01$). These results suggest that negative emotional reactions toward technology can hinder perceptions of competence.

Table 3. Descriptive Statistics and Pearson Correlation Coefficients

Variable	M	SD	1	2	3	4	5	6	7	8	9	10	11
1. Grade	-	-	-										
2. Gender [a]	-	-	.07	-									
3. PC [b]	-	-	.45**	-.03	-								
4. Optimism	38.12	5.03	.18**	.12**	.14**	-							
5. Innovativeness	21.83	3.60	.13**	.19**	.13**	.48**	-						
6. Discomfort	34.23	4.14	-.11*	-.04	-.18**	-.17**	-.21**	-					
7. Insecurity	31.98	5.29	-.05	-.17**	-.07	-.19**	-.21**	.42**	-				
8. DDC	27.27	5.94	.19**	.10*	.15**	.31**	.47**	-.13**	-.15**	-			
9. TC	26.14	4.94	.18**	.19**	.21**	.36**	.48**	-.16**	-.13**	.68**	-		
10. TPC	27.99	4.92	.22**	.03	.13**	.27**	.28**	-.06	.01	.61**	.65**	-	
11. IE	21.22	3.73	.28**	.01	.16**	.30**	.28**	-.05	.02	.48**	.57**	.71**	-

Note: *p < .05, **p < .01, [a] 0= Female, 1= Male, [b] 0= No, 1= Yes, PC= Personal computer, DDC= Design and development competence, TC= Technical competence, TPC= Techno pedagogical competence, IE= Implementation and evaluation

Computer ownership showed significant moderate positive correlations with all competency dimensions, especially technical skills ($r = .21$, $p < .01$) and implementation-evaluation competence ($r = .16$, $p < .01$), indicating access to personal technology is associated with stronger perceived skills. The grade was also positively correlated with all technology competencies, with the strongest correlation observed with implementation and evaluation competence ($r = .28$, $p < .01$). Gender showed relatively weak correlations, with a modest positive correlation between being female and optimism ($r = .12$, $p < .01$) and innovativeness ($r = .19$, $p < .01$).

These results indicate that higher optimism and innovativeness are positively related to technological competence, whereas discomfort and insecurity are negatively related. In addition, access to personal technology and higher grades are associated with greater perceived technological skills. A structural equation modeling (SEM) analysis was conducted as part of the advanced statistical procedures to explore the predictive relationships among these variables further.

Structural Equation Model Analysis Results

This study conducted a structural equation modeling (SEM) analysis to examine the effect of technological readiness on digital material design competencies among preservice teachers. The model included grade level, gender, and personal computer ownership as control variables. The fit indices indicated that the model fit the data well. Specifically, the chi-square to degrees of freedom ratio (χ^2/df) was found to be 3.52, which falls within the acceptable range ($2 \leq \chi^2/df \leq 5$). Additionally, RMSEA = .07 ($0 \leq$ RMSEA $\leq .08$), SRMR = .045 ($0 \leq$ SRMR $\leq .08$), CFI = .95 ($.90 \leq$ CFI ≤ 1.00), IFI = .95 ($.90 \leq$ IFI ≤ 1.00), and TLI = .95 ($.90 \leq$ TLI ≤ 1.00) all support the overall goodness of fit of the model (Hu & Bentler, 1999; Kline, 2016). The path diagram of the model is presented in Figure 1. The standardized path coefficients, standard errors, critical ratios, and significance levels of the hypothesized relationships are detailed in Table 6.

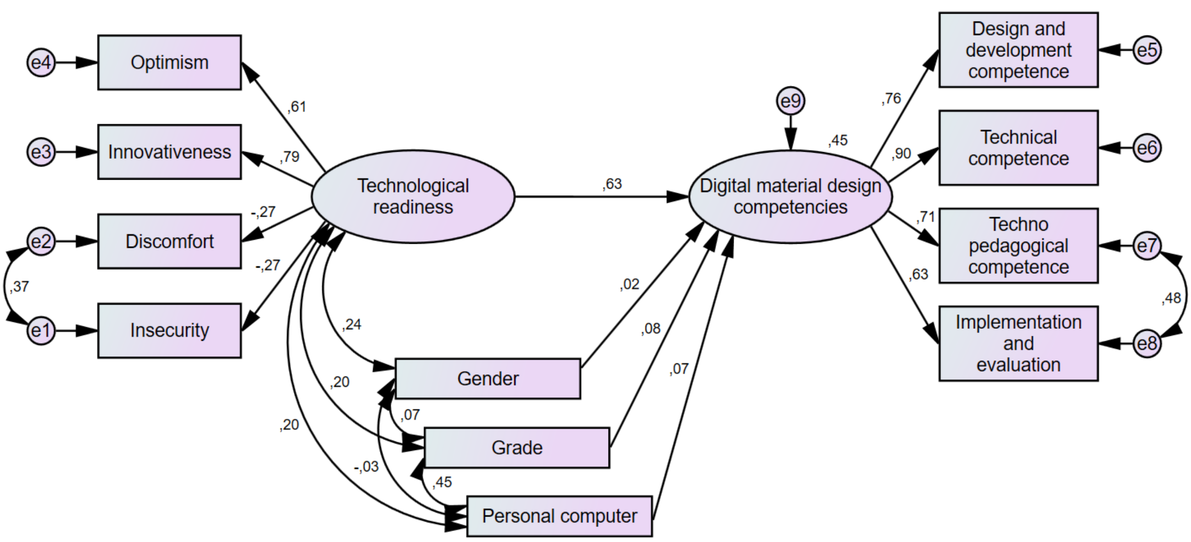

Figure 1. Structural Equation Model, χ^2=119.51, df= 34, p<.001

Table 6. Path Estimates in the Structural Equation Model (R^2 = .45)

Dependent		Predictor	β	S.E.	C.R.	P	%95 CI	
							Lower	Upper
Technological readiness	--->	Digital material design competencies	0,63	0,11	8,50	***	0,51	0,74
Gender	--->	Digital material design competencies	0,02	0,47	0,36	0,72	-0,09	0,12
Grade	--->	Digital material design competencies	0,08	0,18	1,67	0,10	-0,03	0,17
Personal computer	--->	Digital material design competencies	0,07	0,49	1,43	0,15	-0,03	0,16

Note: ***$p < .001$

As shown in Table 6, technological readiness was found to significantly and positively predict digital material design competencies ($\beta = .63$, $p < .001$). This finding suggests that preservice teachers who perceive themselves as technologically ready are likelier to demonstrate higher competencies in designing digital materials. The explained variance ($R^2 = 0.45$) demonstrates the model has strong explanatory power for digital material design competencies. In contrast, the control variables, gender ($\beta = .02$, $p = .72$), grade level ($\beta = .08$, $p = .10$), and personal computer ownership ($\beta = .07$, $p = .15$)—did not exhibit statistically significant effects on digital material design competencies. Although these variables were not significant predictors, their inclusion in the model is important for controlling potential confounding effects. In summary, the model reveals a substantial pathway from technological readiness to digital material design competencies, underscoring the central role of technological preparedness in developing digital content design skills.

Discussion

This study aimed to examine the predictive role of technological readiness on digital material design competencies among Turkish pre-service teachers, using structural equation modeling (SEM). Data were collected from 506 students at a public university in Türkiye, and validated scales were used to measure technological readiness and design competencies. The SEM model controlled for gender, grade level, and personal computer ownership. Results showed that technological readiness significantly and positively predicted digital material design competencies, while the control variables were not significant.

Main Findings

The primary hypothesis of this study proposed that technological readiness would significantly and positively predict digital material design competencies among pre-service teachers, even when gender, grade level, and personal computer ownership were statistically controlled. The structural equation modeling analysis fully supported this hypothesis ($\beta = .63$, $p < .001$), indicating a robust and positive relationship between readiness and digital design competencies.

This finding reinforces the idea that attitudes and psychological dispositions toward technology, particularly optimism and innovativeness, are critical drivers of meaningful engagement with digital content creation. Furthermore, the importance of digital material design competencies extends beyond pre-service teachers to in-service educators. Demircioğlu and Yurt (2024) found that classroom teachers' digital material design skills, assessed using the Digital Material Design Competencies Scale (Göçen Kabaran & Uşun, 2021), positively correlated with their professional competence perceptions, with design and development skills as a significant predictor. This suggests that proficiency in creating pedagogically sound digital materials not only enhances pre-service teachers' readiness for technology-integrated classrooms, as demonstrated in this study, but also bolsters in-service teachers' professional confidence. The consistency of these findings across teacher populations highlights the need for teacher education programs to prioritize digital material design training alongside fostering technological readiness, thereby supporting both pre-service preparation and ongoing professional development. Consequently, pre-service teachers with strong emotional and cognitive readiness for technology are better equipped to develop competencies for designing effective digital materials.

The observed predictive effect of technological readiness aligns with previous research suggesting that affective variables can enhance digital performance more strongly than access or experience alone (Blayone, 2018; Kim et al., 2019). Similar to findings by Álvarez-Marín et al. (2023), optimism and innovativeness were found to be positively associated with design competency subdimensions, supporting the argument that positive technology attitudes drive both engagement and experimentation. Moreover, the result supports Pozas et al. (2022), who argue that teachers with higher readiness profiles are more adaptive and less stressed in technology-intensive teaching environments. This suggests that readiness does not merely reflect personality or attitude, it has tangible consequences for competency development.

This study distinguishes itself from prior work by testing the hypothesis using a structural equation modeling (SEM) framework while controlling for key demographic variables. Whereas earlier studies tended to treat readiness or competency as isolated constructs, this research integrated them within a unified model, showing that readiness explains a substantial portion of variance in design competencies ($R^2 = .45$). Furthermore, the study fills a notable gap in the literature by focusing on Turkish pre-service teachers, a population underrepresented in EdTech readiness studies, and showing that attitudinal factors may have greater impact than structural ones (e.g., ownership or gender). This not only adds cultural nuance to the global discourse but also highlights the need for readiness-focused interventions in teacher education programs.

Control Variables Analysis

Gender

Gender did not significantly predict digital material design competencies when technological readiness was controlled ($\beta = .02$, $p = .72$), indicating that male and female pre-service teachers exhibited similar competency levels when they shared comparable attitudes and readiness toward technology. This finding aligns with recent research by Campos and Scherer (2023), which suggests that gender differences in digital skills are narrowing in higher education, especially in contexts with standardized, technology-integrated curricula. It also supports Redecker's (2017) DigCompEdu framework, which highlights how equitable access and structured training can help close traditional digital skill gaps. However, the result contrasts with earlier studies (e.g., Campos & Scherer, 2024; Vázquez-Cano et al., 2017) that reported gender-based disparities in digital literacy or technical abilities. A key distinction in the present study is its inclusion of affective-motivational variables such as technological readiness, which may account for the absence of gender-related variance. Thus, the findings contribute to the growing body of literature suggesting that in environments emphasizing readiness and equity in training, demographic factors like gender may play a diminished role in predicting digital teaching competencies.

Individual Computer Ownership

Although pre-service teachers who owned a personal computer initially demonstrated higher digital design competency scores, this effect became non-significant in the structural equation model after accounting for technological readiness ($\beta = .07$, $p = .15$). This indicates that personal access to digital devices alone does not guarantee competence in digital material design unless it is accompanied by attitudinal readiness, such as confidence and willingness to engage with new technologies. This finding aligns with the Technology Readiness Index (Parasuraman, 2000), which highlights psychological drivers, such as optimism and innovativeness, as key determinants of effective technology use.

The critical role of attitudinal factors is further evidenced by the widespread sense of unpreparedness among teacher candidates. Recent studies reveal that many pre-service teachers feel ill-equipped for digital teaching: Dolezal et al. (2025) found that roughly half of surveyed pre-service teachers "do not feel sufficiently prepared by their study program to foster digital competence." This preparation gap is compounded by research demonstrating that teachers' confidence and perceived readiness strongly influence their technological competence. Dai et al. (2023) report that pre-service teachers' ICT self-efficacy has a strong positive association with their digital competence, while infrastructure support has a weaker, though still positive, effect. Similarly, Marais (2023) emphasizes that during COVID-19, many students lacked the skills to effectively use even the technology that institutions provided, underscoring the dual importance of access and competence.
Pre-service teachers themselves articulate these challenges through their feedback and experiences. In focus groups, advanced teacher candidates expressed eagerness to learn digital skills but requested more structured collaboration and guidance to reach professional-level digital material design capabilities (Dai et al., 2023). When provided with dedicated support through a 14-week course, the majority of students "could successfully experience [the] digital material design process" and felt "improved enough to practice teaching with digital materials and resources" (Kabaran & Altan, 2022). However, they also encountered concrete technical obstacles, with students noting difficulties such as "Prezi is very difficult to use… Organizing templates… are very difficult" and concerns about premium features requiring payment in platforms like Canva. Such feedback highlights what Kabaran & Altan (2022) call the teacher's "double challenge" of mastering both technology use and effective pedagogical design with digital tools.

Unlike studies in low-resource settings (e.g., Mallillin et al., 2020), where limited access to technology posed a significant barrier, the current study, conducted in a relatively high-access environment (73.7% ownership rate), suggests that attitudinal factors outweigh access in predicting digital competence. In practice, this means teacher education programs should not only provide devices and software to ensure students aren't limited to basic tools like phones in the classroom (Dolezal et al., 2025), but also embed hands-on, scaffolded instruction in material design to build confidence and competence simultaneously. When programs implement such comprehensive approaches, pre-service teachers report significant gains, but when they don't, many candidates feel they lack both access and readiness for digitally-rich teaching. These results underscore the need to embed readiness-building strategies within teacher education programs, especially in settings where technological infrastructure is already available. They also imply that resource-provision efforts should be coupled with psychological and pedagogical support to foster meaningful and sustained learning outcomes, addressing both external factors (access to technology and support) and internal factors (attitudes, confidence, and thorough training) simultaneously.

Grade Level

Grade level was not a significant predictor of digital material design competencies when technological readiness was included in the model ($\beta = .08$, $p = .10$), despite a moderate correlation found in initial bivariate analyses ($r = .28$, $p < .01$). This suggests that although upper-grade students—particularly those in their fourth year—tend to demonstrate more advanced design skills, these improvements are likely attributable to prolonged exposure to technology-rich learning environments rather than mere academic progression. This finding is consistent with Koyuncuoğlu (2022), who noted that project-based courses and sustained engagement with digital tools enhance design competencies. The absence of a significant direct effect in the structural equation model implies that, once technological readiness is considered, grade level loses its predictive value. Therefore, fostering technological readiness early in teacher education programs may be equally, if not more, critical than relying on passive competency development over time, highlighting the importance of embedding structured, psychologically informed interventions throughout all stages of teacher training.

Limitations and Future Directions

This study, while offering meaningful insights, is not without limitations. First, it utilized a cross-sectional design, which restricts causal inference. Longitudinal studies are needed to examine how technological readiness and design competencies evolve over time. Second, data were collected from a single institution, limiting generalizability across diverse educational contexts in Türkiye. Third, although the study controlled for key demographic variables, it did not account for factors such as digital self-efficacy, frequency of technology use, or prior training experiences. Future research should incorporate these variables and explore potential mediators or moderators to gain a deeper understanding of the mechanisms linking readiness and competency.

Conclusion

This study demonstrates that technological readiness is a significant and robust predictor of digital material design competencies among Turkish pre-service teachers, even when demographic factors such as gender, grade level, and computer ownership are accounted for. By integrating readiness theory and employing structural equation modeling, the study fills a notable gap in the literature and emphasizes the psychological dimensions of technology integration in teacher education. These findings suggest that attitudes such as optimism and innovativeness are not only desirable traits but essential foundations for developing advanced digital teaching skills.

Practical Recommendations

Teacher education programs should go beyond technical training and invest in cultivating technological readiness early in the curriculum. Courses should include opportunities to foster optimism and innovativeness, such as project-based learning, design tasks, and reflective practices around technology use. Policymakers should also ensure that efforts to provide device access are paired with interventions that support teachers' emotional and cognitive readiness for technology. Finally, educators should treat digital material design not merely as a technical task but as a pedagogical process that requires confidence, creativity, and adaptability.

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

***Ethics Statement*:** The study was approved by the Eskişehir Osmangazi University Social and Humanities Research Ethics Committee (Date: 12.10.2022; Issue Number: 2022-15).

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

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Abstract

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

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

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Introduction

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

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

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

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

Theoretical Framework

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

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

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

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

Table 1. Theoretical Framework Summary

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

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

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

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

Literature Review

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

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

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

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

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

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

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

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

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

Method

Participants

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

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

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

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

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

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

Instrument

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

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

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

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

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

Procedures

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

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

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

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

Following the EFA, confirmatory factor analysis (CFA) was performed with data from a separate sample of 340 participants to test the factor structure identified in the EFA. CFA aims to verify the measurement model and assess its fit to the data. Model fit was evaluated using various indices, including $\chi2/df$, standardized root mean residual (SRMR), root mean square error of approximation (RMSEA), comparative fit index (CFI), and Tucker-Lewis index (TLI), as recommended by Hu and Bentler (1999).

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

Results

Exploratory Factor Analysis Results

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

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

Table 4. Exploratory Factor Analysis Results for SRAILS Dimensions

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

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

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

Confirmatory Factor Analysis Results

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

Table 5. Confirmatory Factor Analysis Results and Reliability Statistics

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

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

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

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

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

Descriptive Statistics and Factor Correlations for the SRAILS

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

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

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

**p<0,01; N=340

Criterion-Related Validity Evidence

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

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

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

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

N = 287, ** p < .01

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

Discussion

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

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

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

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

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

Study Limitations and Future Research Directions

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

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

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

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

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

Conclusion

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

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

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

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

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

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

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

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

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Appendix

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

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

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

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