International Electronic Journal of Mathematics Education
2025, 20(3), em0832
e-ISSN: 1306-3030
https://www.iejme.com

MODESTUM

Research Article **OPEN ACCESS**

Integrating generative AI into STEM education: Insights from science and mathematics teachers

Abdulla Al Darayseh [1]*, Nazan Mersin [2]

[1] Emirates College for Advanced Education, UAE
[2] Istanbul Medeniyet University, TÜRKIYE
***Corresponding Author:** derayseh@yahoo.com

Citation: Al Darayseh, A., & Mersin, N. (2025). Integrating generative AI into STEM education: Insights from science and mathematics teachers. *International Electronic Journal of Mathematics Education, 20*(3), em0832. https://doi.org/10.29333/iejme/16232

ARTICLE INFO

Received: 25 Dec 2024

Accepted: 12 Mar 2025

ABSTRACT

This study investigates the perceptions of STEM teachers regarding the integration of generative artificial intelligence (AI) applications into classroom settings, using the extended Technology Acceptance Model (TAM) as the framework. The study examines self-efficacy, anxiety, perceived ease of use, expected benefits, attitudes, and behavioral intentions toward AI applications. Data was collected from 448 mathematics and science teachers across various Turkish provinces through an online survey. Results revealed a generally positive attitude toward AI, with male teachers exhibiting higher self-efficacy and perceived ease of use compared to female teachers. However, no significant differences were found across other TAM dimensions, such as stress, anxiety, and expected benefits, based on gender, age, or teaching experience. These findings suggest that while STEM teachers are generally open to AI adoption, targeted interventions are needed to address gender disparities and improve ease of use.

Keywords: artificial intelligence, STEM teachers, technology acceptance model, self-efficacy, anxiety and stress

INTRODUCTION

In recent years, there has been a growing interest in adapting Artificial Intelligence (AI) into education. AI technologies have the potential to revolutionize teaching and learning by providing personalized and adaptive learning experiences for students. One area where AI has shown promising results is in the field of Science, Technology, Engineering, and Mathematics (STEM) education (Lee et al., 2023).

STEM education prepares students for the future, focusing on developing critical thinking, problem-solving, and analytical skills. However, traditional classroom approaches often struggle to provide individualized attention to each student due to time constraints and limited resources. This is where Generative AI can significantly impact (Baidoo-Anu & Owusu, 2023; Kasneci et al., 2023; Lee et al., 2023; Qadir, 2022).

Generative AI uses algorithms and machine learning techniques to generate content, such as text, images, videos, or music. By leveraging the power of Generative AI, educators can create interactive and engaging learning experiences that cater to each student's different needs and interests. This can benefit STEM classes, where complex concepts and abstract ideas can be better understood through interactive visualizations and simulations (Chen et al., 2020).

Despite the great potential offered by AI-supported learning, it does not guarantee the quality of teaching because of teachers' readiness (UNESCO, 2019). Furthermore, the effective adoption of new technologies is closely linked to the attitudes of STEM teachers towards them. Apprehension about adopting new techniques may hinder teachers' willingness to embrace technology in their classroom practices (Hébert et al., 2021; Tallvid, 2016).

This study aims to explore the insights of STEM Turkish teachers regarding integrating Generative AI into their classrooms by investigating the external factors using the extended TAM acceptance model.

LITERATURE REVIEW

Artificial intelligence is a computer system designed to emulate the neural processes employed by humans for understanding, learning, thinking, and executing appropriate actions. It possesses the capability to perform tasks typically associated with human intelligence, including visual perception, speech recognition, decision-making, and language translation (Stone et al., 2016). The foundation of AI lies in the belief that intelligence can be so precisely defined that a machine can replicate it. In its most sophisticated manifestation, AI exhibits skills like learning, recognizing situations, problem-solving, and engaging in natural language communication, distinguishing it from other computer programs through its capacity for self-learning (Kok et al., 2009). According to Nikitas et al. (2020), AI is a concept still in its early stages, with the potential for evolution and the enhancement of resource efficiency across various fields.

Generative Pre-trained Transformer (GPT) has recently been hailed as a world changer. GPT technology utilizes many publicly available digital content data to process and generate humanlike text. This technology showcases creativity by producing convincing written content across various topics. GPT models are adept at engaging in humanlike conversations with customers and have found successful applications in various work tasks. The launch of ChatGPT in November 2022 precipitated panic among some educators while prompting qualified enthusiasm from others. Under the umbrella term Generative AI, ChatGPT is an example of a range of technologies for delivering computer-generated text, images, and other digitized media (Grassini, 2023).

According to Chen et al. (2020) AI has potential to both support and transform the field of education. It provides personalization, customization, and optimization of learning experiences for students. For example, AI can analyze student data to diagnose learning problems, provide targeted feedback, and recommend personalized learning paths. AI can also be used as a research tool, for instance, to analyze large educational data sets and help researchers better understand student learning and identify effective teaching practices.

AI has begun to be considered as a fundamental pillar in STEM education, and it plays an important role in assisting teachers in their roles as facilitators and assessors of learning. This is demonstrated by the possibilities for analysing big data about the learning process collected from students, teachers, and schools. AI can enhance student engagement and motivation through personalized learning experiences. It provides access to vast amounts of information, resources, and simulations that can support and augment traditional teaching methods (Bhutoria 2022; Cukurova et al., 2012). In essence, AI can improve STEM education by making it more engaging, accessible, efficient, and effective. Zhao et al. (2019) assert that the implementation of AI-based teaching positively influences students' academic achievement and addresses challenges related to forgetting learned material. Additionally, Topal et al. (2021) posits that chatbots contribute to the enhancement of STEM teaching, leading to improved student performance and learning outcomes. Furthermore, the utilization of an AI-enhanced scaffolding system by teachers is believed to positively affect the scientific writing skills of STEM students (Kim & Kim, 2022).

Based on recent studies, there is a potential lack of awareness among STEM educators regarding the utilization of AI. It is essential to enhance this awareness to foster an understanding of the fundamental aspects of AI and its application in STEM education (AlKanaan, 2022; Shin & Shin, 2020). Teachers need comprehensive preparation to address challenges such as insufficient educational resources and ineffective teaching methods associated with AI. This preparation is crucial for the effective incorporation of AI-related subjects into teaching practices (Lindner & Romeike, 2019).

Technology Acceptance Model (TAM)

This model was developed to explain the behaviors associated with the adoption of technology. According to this model, the utilization of AI can be explained through the behavioral intentions resulting from conscious decision-making. These intentions are shaped by two main factors: the expected benefits and the perceived ease of use. By addressing these factors, developers of technological applications can exert better control over teachers' attitudes towards these applications, subsequently influencing their behavioral intentions and actual usage. Research conducted by Saade et al. (2007) supports the notion that the Technology Acceptance Model (TAM) serves as a robust theoretical foundation, applicable to the study of digital education and its various applications. According to TAM, the benefits of AI usage are gauged by the extent to which STEM teachers believe that AI applications enhance their performance, while the perceived ease of use is linked to the belief that using these applications won't require additional effort. The model posits that attitudes towards usage act as a guiding force for future behavior, creating intentions that ultimately manifest in specific actions. These usage attitudes reflect teachers' evaluative sentiments, either positive or negative, towards engaging in a particular manner (Lew et al., 2019).

In accordance with this model, the actual implementation of AI is directly or indirectly influenced by teachers' behavioral intentions and attitudes, as well as the anticipated benefits and ease of use. Additionally, external factors may impact usage intentions and real-world application by affecting the perceived benefits and usability, as outlined in the model proposed by Davis et al. (1989).

TAM has developed over time, incorporating various external factors like social impact, experience, anxiety and stress, self-satisfaction, and self-efficacy (Guner & Acarturk, 2020). Numerous prior studies have affirmed the model's efficacy in predicting acceptance and interpretative factors related to the use of technological applications (Al Darayseh, 2023). These studies have also highlighted the model's significant role in predicting teachers' interactions and behavioral tendencies in e-learning environments, augmented reality applications, and metaverse technology (Aburbeian et al., 2022; Asiri & El Aasar, 2022; Durak, 2019).

This study relies on the technology acceptance model (TAM), because of its simplicity, its applicability to the context and its efficiency in predicting the adoption of technologies in educational settings.

The research model shown in **Figure 1** was developed based on previously reviewed literature as well as the pillars of TAM to determine factors influencing the application of AI in science teaching. Based on that, the present study adopted the six factors of SA, SE, PU, EU, A, and BI. According to the literature, teachers' PU, EU, and attitudes towards adopting technologies for teaching could have effects on their BI; their EU and PU also influence their attitudes toward adopting AI applications in STEM teaching activities (Kao & Tsai, 2009; Teo, 2019; Wang & Wang, 2009). Previous research has also found that SE has a direct impact on teachers' PEU and attitudes toward technology adoption (Kao & Tsai, 2009; Ursavaş et al., 2019; Wang & Wang, 2009). A higher SE implies a higher perceived EU and A, which may lead to the use of AI applications for teaching. Moreover, researchers have also

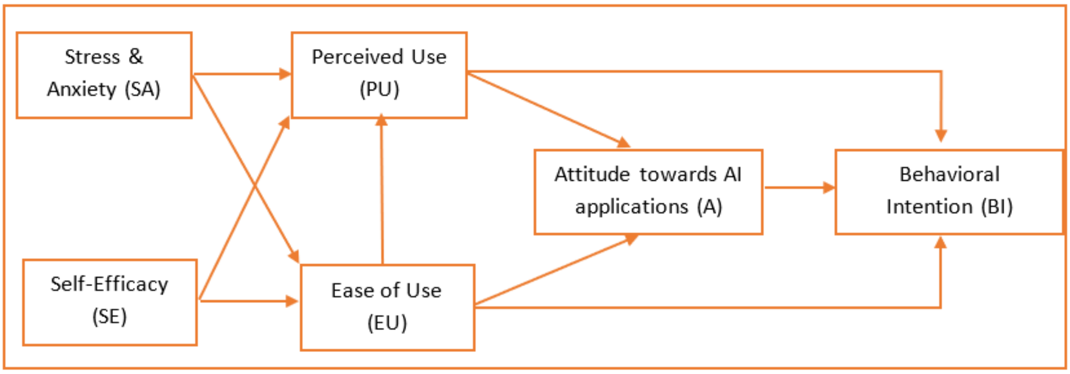

Figure 1. TAM used in this study (Source: Authors' own elaboration)

pointed out that SE directly links to SA (Kao & Tsai, 2009; Sánchez-Prieto et al., 2017). According to some studies, when teachers lack the ability to use new technologies, they may have negative perceptions of them (e.g., anxiety). This could influence their cognition of the functions and their attitude towards using the technologies (Sánchez-Prieto et al., 2017). Teachers may find it easier to use technologies to assist with their teaching when they are more familiar with or confident in using them; on the other hand, if teachers experience frustration or negative feelings, it may influence their attitude toward the adoption of technologies (Sánchez-Prieto et al., 2017; Wang & Wang, 2009).

Research Questions

RQ1 What is the level of STEM teachers' self-efficacy, anxiety and stress, ease of use, attitude, expected benefit and behaviours intentions towards using artificial intelligence on TAM scale?

RQ2 What is the relationship between the variables of STEM teachers' self-efficacy, anxiety and stress, expected benefits, ease of use, attitudes towards artificial intelligence, and intentions to use artificial intelligence?

RQ3 Considering the components of TAM, what are the factors affecting the effectiveness of using artificial intelligence applications in STEM education?

RQ4 Do the scores obtained from the sub-factors of TAM scale show a significant difference according to the gender of STEM teachers?

RQ5 Do the scores obtained from the sub-factors of TAM scale show a significant difference according to the branches of STEM teachers?

RQ6 Do the scores obtained from the sub-factors of TAM scale show a significant difference according to the age of STEM teachers?

RQ7 Do the scores obtained from the sub-factors of TAM scale show a significant difference according to the academic levels of STEM teachers?

RQ8 Do the scores obtained from the sub-factors of TAM scale show a significant difference according to the teaching experience of STEM teachers?

METHODOLOGY

This study used a structural equation modeling (SEM) approach to develop a research model to represent the relationships among the variables of intention to use AI tools, attitudes toward the use of AI tools in teaching mathematics, anxiety, perceived usefulness, and perceived ease of use. Data were collected through a questionnaire to elicit demographic information and participants' responses to multiple items measuring each construct reflected in the research model. Informed consent was obtained from participants for all cases and all ethical requirements were followed.

Participants

In this study, 448 mathematics and science teachers from various provinces of Turkey participated during the 2023-2024 academic year. Detailed information about the participants is presented in **Table 1**. Upon reviewing the **Table 1**, it is observed that the sample consists of 79.2% female and 20.8% male teachers. Additionally, 64.7% of the sample comprises mathematics teachers, while 35.3% are science teachers. Most of the teachers (88.4%) fall within the 21-40 age range. Moreover, 67.4% of the teachers have 0-10 years of teaching experience. Regarding the educational level of the participants, it is determined that 69.6% hold a bachelor's degree, 26.6% have a master's degree, and 17.9% possess a doctoral degree.

Instrument of the Study

In this study, a questionnaire developed by Al Darayseh (2023) was used. This questionnaire was designed in the light of the objectives and questions of the study after reviewing previous studies such as those conducted by Guner and Acarturk (2020), Wang et al. (2021) and Asiri and El aasar (2022). The questionnaire is divided into three sections: The first section includes an

Table 1. Demographic information

Demographic Profile	Classification	Number	Percent (%)
Department	Mathematics Teacher	290	64.7 %
	Science Teacher	158	35.3 %
Gender	Male	93	20.8 %
	Female	355	79.2 %
Age	21-30	212	47.3 %
	31-40	184	41.1 %
	41-50	45	10 %
	51 and over	7	1.6 %
Teaching years	0-5	185	41.3 %
	6-10	117	26.1 %
	11-15	80	17.9 %
	16-20	33	7.4 %
	21 and over	33	7.4 %
Academic Level	Bachelor's degree	312	69.6
	Master's Degree	119	26.6
	PhD Graduate	17	3.8

Table 2. Cronbach's alpha coefficient to measure the stability of the study tool

	Number of Items	Cronbach's Alpha Coefficient
Self-efficacy	4	0.70
Stress and Anxiety	5	0.63
Expected Benefits	9	0.85
Ease of Use	3	0.79
Attitudes Towards AI	3	0.70
Behavioural Intention	4	0.82
Total	28	0.92

introduction and general information about the topic of the study, while the second section includes demographic information such as gender, teaching experience and academic level. The third part includes the TAM scale, which contains 32 items measuring 6 factors. The first factor consists of 5 items and measures self-efficacy towards the use of artificial intelligence, the second factor consists of 6 items and measures anxiety and stress towards using artificial intelligence, the third factor consists of 9 items and measures expected benefits of using artificial intelligence in teaching, the fourth factor consists of 4 items and measures ease of use, the fifth factor consists of 4 items and measures attitude towards artificial intelligence applications, and the sixth factor consists of 5 items and measures behavioural intention to use AI in teaching. It was also decided to use a five-point Likert scale to rate the response level. A response of one means strongly disagree and five means strongly agree. This questionnaire developed by Al Darayseh (2023) was first adapted to Turkish language.

The method proposed by Brislin (1980) was taken as a basis for adapting the scale into Turkish. It consists of five main steps: translation of the scale into the target language, evaluation of the translation into the target language, retranslation into the source language, evaluation of the retranslation into the source language, and final evaluation with experts. This evaluation process was carried out by experts who have a good command of both English and Turkish languages.

Realibity of the Study Instrument

The reliability coefficient of the study tool was obtained using Cronbach's alpha and the results are shown in **Table 2**. Cronbach's alpha coefficient values for the study areas and the overall scale are all greater than 0.7 except for the stress and anxiety factor, indicating that the instrument has a high degree of reliability. This rate is appropriate for the purposes of the present study.

Data Collection and Analysis

The data used in the study were collected using Google form. TAM was prepared online on Google form. This scale link was shared directly with science and mathematics teachers, various WhatsApp groups and groups on various social media platforms. The scale link on Google forms was open to everyone for about 2 months and a total of 448 STEM teachers, 290 mathematics teachers and 158 science teachers, filled out this scale in two months.

In the process of data analysis, firstly, it was checked whether there were any deficiencies and outliers in the collected data. SPSS 20.0 programme and AMOS 6.0 were used for data analysis. According to the predefined research questions, firstly, descriptive statistics directly related to the first research question were conducted to find out STEM teachers' self-efficacy, anxiety and stress, expected benefits, ease of use, attitudes towards AI, and intentions to use AI applications in their lessons. Skewness and kurtosis were considered to verify the normality of the measured variables and Pearson's product-moment correlation coefficient was used for correlation analysis.

Secondly, correlation analysis was conducted to find the relationship between the variables of teachers' self-efficacy, anxiety and stress, expected benefits, ease of use, attitudes towards AI, and intentions to use AI applications, and this is related to the second research question. Thirdly, to measure STEM teachers' intentions to use AI tools, structural equation modelling analysis was conducted using AMOS 6.

Table 3. Descriptive statistics on STEM teachers' self-efficacy, stress and anxiety, expected benefits, ease of use, attitudes towards AI, behavioural intention

		N	Aritmetic Mean	Total Aritmetic Mean
Self-efficacy	Math Teacher	210	3.56	3.63
	Science Teacher	158	3.67	
Stress and Anxiety	Math Teacher	210	3.64	3.68
	Science Teacher	158	3.76	
Expected Benefits	Math Teacher	210	3.88	3.88
	Science Teacher	158	3.89	
Ease of Use	Math Teacher	210	2.90	2.94
	Science Teacher	158	2.96	
Attitudes Towards AI	Math Teacher	210	3.92	3.92
	Science Teacher	158	3.92	
Behavioural Intention	Math Teacher	210	3.72	3.73
	Science Teacher	158	3.75	
Total	Math Teacher	210	3.67	3.69
	Science Teacher	158	3.72	

Table 4. Simple correlation between TAM factors

	Self-efficacy	Stress and Anxiety	Expected Benefits	Ease of Use	Attitudes Towards AI	Behavioural Intention
Self-efficacy	1					
Stress and Anxiety	.450**	1				
Expected Benefits	.389**	.522**	1			
Ease of Use	.684**	.413**	.320**	1		
Attitudes Towards AI	.509**	.524**	.577**	.415**	1	
Behavioural Intention	.534**	.550**	.615**	.451**	.651**	1

*Significant at 0.05; **Significant at 0.01

RESULTS AND DISCUSSION

RQ1. What is the Level of STEM Teachers' Self-Efficacy, Anxiety and Stress, Ease of Use, Attitude, Expected Benefit and Behaviours Intentions Towards Using Generative Artificial Intelligence in TAM Scale?

The descriptive statistics of STEM teachers regarding the sub-dimensions of TAM scale are given in **Table 3**. Accordingly, it is seen that teachers' attitudes towards using artificial intelligence applications (M = 3.92) and expected benefits dimensions (M = 3.88) have the highest meaning. From this point of view, it can be said that teachers have a positive attitude towards artificial intelligence applications and believe that they will be useful at a high level (Al Darayseh, 2023). On the other hand, it was determined that the mean score of the sub-dimension of the ease of use of artificial intelligence applications (M = 2.94) was at the lowest level. Therefore, it can be said that teachers might face challenges in using AI effectively. Self-efficacy and behavioral intention are moderately high, showing confidence and willingness to use AI, though stress and anxiety levels indicate potential hurdles. These findings suggest that while teachers are tending to adopt AI, additional support and training are necessary to improve ease of use and reduce anxiety. Addressing these concerns can facilitate smoother integration of AI into STEM education.

RQ2. What is the Relationship Between the Variables of STEM Teachers' Self-Efficacy, Anxiety and Stress, Expected Benefits, Ease of Use, Attitudes Towards Artificial Intelligence, and Intentions to Use Artificial Intelligence?

To ensure that there were no multiple correlations between the factors in the model, a simple correlation factor was used through the heterotrait-monotrait ratio test, and the results in **Table 4** indicate that the simple correlation factor values among all factors are below 0.9, indicating no multiple correlation between variables (Hair et al., 2017). Based on this result, the constructions in the model have discriminant validity. In this way, convergent and discriminant validity assessments revealed constructs in the model to be valid. Thus, the latent scores of the constructs in the model were obtained and used to assess the structural model.

RQ3. Considering the Components of TAM, What Are the Factors Affecting the Effectiveness of Using Artificial Intelligence Applications in STEM Education?

Table 5 shows the results of the path analysis to identify the factors influencing the use of AI applications in STEM education according to the components of TAM's acceptance model and the data are also represented in **Figure 2**.

The findings show that 6 of the 11 paths with standardised regression coefficient have a statistically significant and positive correlation: SA on PU: 0.666, SE on EU: 0.986, EU on A: 0.434, PU on A: 0.640, A on BI: 0.768, SA on SE: 0.666

Accordingly, the model was tested again after the non-significant paths were removed. Accordingly, the results of the new model are given in **Figure 2** and **Table 5**.

Table 5. Standardized path coefficient for tested model

Hypothesis	Path	Standart Error	Standart Regression	P values	Results
H1	SA…EU (KS-KK)	0.124	-0.040	0.643	Reject
H2	SA…PU(KS-BY)	0.181	0.666	***	Accepted
H3	SE…EU (ÖY-KK)	0.091	0.986	***	Accepted
H4	SE…PU (ÖY-BY)	0.609	1.114	0.192	Reject
H5	EU…PU (KK-BY)	0.697	-1.123	0.159	Reject
H6	EU…A (KK-T)	0.037	0.434	***	Accepted
H7	EU…BI (KK-DN)	0.087	0.071	0.392	Reject
H8	PU…A (BY-T)	0.054	0.640	***	Accepted
H9	PU…BI (BY-DN)	0.136	0.100	0.375	Reject
H10	A…BI (T-DN)	0.339	0.768	***	Accepted
H11	SA…SE (KS-ÖY)	0.033	0.666	***	Accepted

***Significant at 0.05

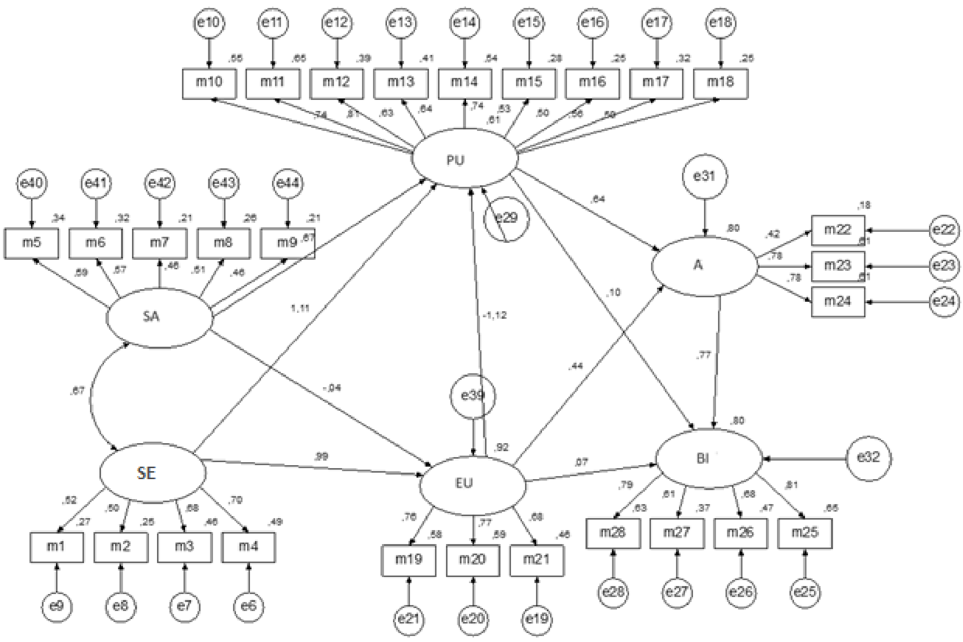

Figure 2. Proposed model (Source: Authors' own elaboration)

Secondly, after the path analysis, the path diagram given in **Figure 3** was obtained. It is seen that the paths in this diagram are statistically significant. The good fit values obtained because of this analysis are given in **Table 6**. According to **Table 6**, the ratio of the chi-square fit index value to the degree of freedom (χ2/sd) is 2.709. This value is called good fit (Byrne, 2010; Schermelleh-Engel et al., 2003; Schumaker & Lomax, 2004). GFI value of 0.85 and AGFI value of 0.80 are acceptable fit indices (Anderson & Gerbing, 1984; Arbuckle, 2007; Çam & Günal, 2016; Çelik & Turunç, 2011; Frias & Dixon, 2005; Harrington, 2009; Jöreskog & Sörbom, 1993; Marcoulides & Schumacher, 2001; Marsh et al., 1988). Therefore, it can be said that the GFI value of .87 and the AGFI value of .84 are at an acceptable level. In addition, CFI values of .90 and above indicate acceptable fit (Hu & Bentler, 2000; Şimşek, 2007; Sümer, 2000; Yılmaz & Çelik, 2009).

The RMSEA value of .0062, which shows the root mean square of approximate errors, indicates a good fit of the model (Byrne, 2010; Schermelleh-Engel et al., 2003; Schumaker & Lomax, 2004).

When the values in **Table 6** are examined, it can be said that the model is acceptable, but to obtain a better model, the analysis was repeated by creating a model again by removing the stress and anxiety factor, which contains negative items in terms of its structure. As a result, the path diagram in **Figure 4** and the good fit values in **Table 7** emerged.

When **Table 7** and **Figure 4** are analysed, it is seen that the paths here are statistically significant. The good fit values obtained because of the final path analysis are given in **Table 7**. According to **Table 7**, the ratio of the chi-square fit index value to the degree of freedom (χ2/sd) is 2.942. This value is called good fit (Byrne, 2010; Schermelleh-Engel et al., 2003; Schumaker & Lomax, 2004). GFI value of 0.89 and AGFI value of 0.86 are good fit indices (Anderson & Gerbing, 1984; Arbuckle, 2007; Çelik & Turunç, 2011; Frias & Dixon, 2005; Harrington, 2009; Jöreskog & Sörbom, 1993; Kline, 1998; Marcoulides & Schumacher, 2001; Marsh et al., 1988; Tanaka & Huba, 1985). However, CFI value of .90 and above indicates good fit (Hu & Bentler, 2000; Sümer, 2000; Yılmaz & Çelik, 2009; Şimşek, 2007).

As a result, it was concluded that the model obtained in **Figure 4** contains higher levels of good fit values than **Figure 3** and the model is more usable.

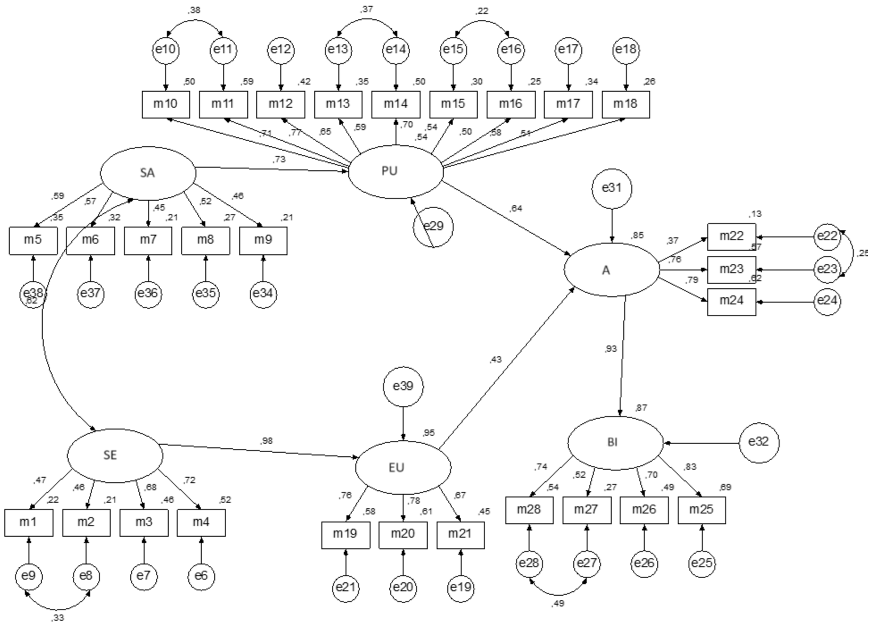

Figure 3. Result of path analysis (Source: Authors' own elaboration)

Table 6. Fitness of goodness of path analysis

Model-of-fit indices	Acceptable Fit Criteria	Actual values	
CMIN/DF	CMIN/DF ≤ 5	2.709	Good fit
RMSEA	RMSEA ≤ 0.08	0.062	Good fit
GFI	GFI ≥ 0.85	0.87	Accepted Fit
AGFI	AGFI ≥ 0.80	0.84	Accepted Fit
CFI	CFI ≥ 0.90	0.89	Accepted Fit

Table 7. The result of the structural model goodness of Fit Test

Model-of-fit indices	Acceptable Fit Criteria	Actual values	
CMIN/DF	CMIN/DF ≤ 5	2.942	Good fit
RMSEA	RMSEA ≤ 0.08	0.066	Good fit
GFI	GFI ≥ 0.85	0.89	Accepted Fit
AGFI	AGFI ≥ 0.80	0.86	Good fit
CFI	CFI ≥ 0.90	0.91	Good fit

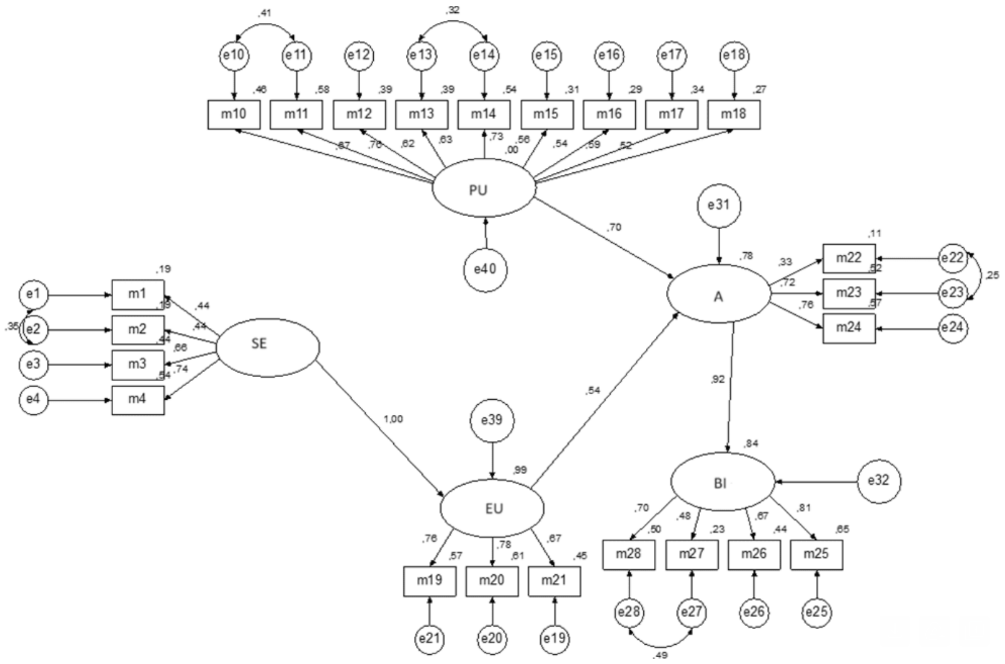

Figure 4. Final path coefficients of the structural model (Source: Authors' own elaboration)

Table 8. T-test result examining the change in the scores STEM teachers received from the sub-dimensions of TAM according to their branches

Factor	Group	N	X	S	df	t	p
SE	M.T	210	3.56	.659	366	-1.637	.102
	S.T.	158	3.68	.648	366		
SA	M.T	210	3.64	.614	366	-1.874	.062
	S.T.	158	3.76	.585	366		
EB	M.T	210	3.88	.515	366	-0.218	.828
	S.T.	158	3.89	.458	366		
EU	M.T	210	2.90	.802	366	-0.699	.485
	S.T.	158	2.96	.762	366		
A	M.T	210	3.92	.605	366	-0.088	.930
	S.T.	158	3.93	.583	366		
BI	M.T	210	3.72	.657	366	-0.436	.663
	S.T.	158	3.75	.635	366		

Table 9. T-test result examining the change in STEM teachers' scores in the sub-dimensions of TAM according to gender

Factor	Group	N	X	S	df	t	p
SE	F	355	3.58	0.651	446	-2.813	.004
	M	93	3.79	0.63	446		
SA	F	355	3.68	0.597	446	-0.394	.694
	M	93	3.71	0.610	446		
EB	F	355	3.89	0.487	446	0.464	.643
	M	93	3.86	0.568	446		
EU	F	355	2.86	0.800	446	-3.884	.000
	M	93	3.22	0.726	446		
A	F	355	3.91	0.583	446	-0.200	.841
	M	93	3.92	0.648	446		
BI	F	355	3.67	0.637	446	-1.673	.095
	M	93	3.76	0.644	446		

RQ4. Do the Scores Obtained from the Sub-Factors of TAM Scale Show a Significant Difference According to the Branches of STEM Teachers?

When **Table 8** is analysed, it is seen that TAM's sub-dimensions of self-efficacy (t_{366} = -1.637, p > 0.05), stress and anxiety (t_{366} = -1.874, p > 0.05), expected benefits (t_{366} = -0.218, p > 0.05), ease of use (t_{366} = -0,699 p > 0. 05), attitude (t_{366} = -0.088, p > 0.05) and intention to use artificial intelligence applications (t_{366} = 0.436, p > 0.05)) sub-dimensions did not create a difference according to the branches of the teachers. In other words, both mathematics teachers and science teachers have similar views in these sub-dimensions.

RQ5. Do the Scores Obtained from the Sub-Factors of TAM Scale Show a Significant Difference According to the Gender of STEM Teachers?

When **Table 9** is analysed, it is seen that there is a significant difference in TAM's sub-dimensions of self-efficacy for using artificial intelligence applications (t_{446} = -2.813, p < 0.05) and ease of use (t_{446} = -0394 p < 0.05) according to gender. This difference is in favour of male teachers in both scales. In other words, male STEM teachers have higher self-efficacy towards artificial intelligence applications, and they find it easier to use the applications than women. On the other hand, it was concluded that there was no difference in the scores obtained from the sub-dimensions of stress and anxiety t_{446} = -0.394 p > 0.05), expected benefits (t_{446} = -0.464, p > 0.05), attitude (t_{446} = -0.200, p > 0.05) and intention to use artificial intelligence applications (t_{446} =-0.436, p > 0.05). This finding may be influenced by several factors. One possible explanation is that males typically receive more encouragement to engage with technology and STEM fields from a young age, leading to greater exposure and experience, which in turn enhances their confidence in using advanced tools like AI. Gender norms and stereotypes often push males towards technical fields, while females may encounter fewer opportunities to build similar confidence, as they are traditionally steered towards non-technical roles (Chan, 2022).

RQ6. Do the Scores Obtained from the Sub-Factors of TAM Scale Show a Significant Difference According to the Age of STEM Teachers?

When analysing **Table 10**, it is evident that the sub-dimensions of the Technology Acceptance Model (TAM)-including self-efficacy in using AI applications ($F_{3\text{-}444}$ = 0.568, p > 0.05), stress and anxiety ($F_{3\text{-}444}$ = 1.558, p > 0.05), expected benefits ($F_{3\text{-}444}$ = 2.451, p > 0.05), ease of use ($F_{3\text{-}444}$ = 0.240, p > 0.05), attitude ($F_{3\text{-}444}$ = 0.073, p > 0.05), and intention to use AI applications ($F_{3\text{-}444}$ = 0.563, p > 0.05)-do not differ significantly based on teachers' age groups. In other words, teachers across different age groups hold similar views on these aspects of AI adoption, indicating that age does not appear to influence perceptions of self-efficacy, ease of use, or attitude toward AI in teaching.

Table 10. One-way ANOVA result examining the change in STEM teachers' scores in the sub-dimensions of TAM according to age

		Sum of Squares	df	Mean Squares	F	Sig.
SE	Between groups	0.727	3	0.242	0.568	0.636
	Within groups	189.273	444	0.426		
	Total	190.000	447			
SA	Between groups	1.672	3	0.557	1.558	0.199
	Within groups	158.876	444	0.358		
	Total	160.549	447			
EB	Between groups	1.854	3	0.618	2.451	0.063
	Within groups	111.968	444	0.252		
	Total	113.822	447			
EU	Between groups	0.462	3	0.154	0.240	0.868
	Within groups	284.524	444	0.641		
	Total	284.986	447			
A	Between groups	0.079	3	0.026	0.073	0.974
	Within groups	159.029	444	0.358		
	Total	159.107	447			
BI	Between groups	0.695	3	0.232	0.563	0.639
	Within groups	182.559	444	0.411		
	Total	183.254	447			

Table 11. One-way ANOVA result examining the change in STEM teachers' scores in the sub-dimensions of TAM according to their teaching experience

		Sum of Squares	df	Mean Squares	F	Sig.
SE	Between groups	1.111	3	0.278	0.652	0.626
	Within groups	188.88	444	0.426		
	Total	190	447			
SA	Between groups	1.094	3	0.274	0.760	0.552
	Within groups	159.45	444	0.360		
	Total	160.54	447			
EB	Between groups	2.115	3	0.529	2.097	0.080
	Within groups	111.707	444	0.252		
	Total	113.822	447			
EU	Between groups	0.226	3	0.057	0.088	0.986
	Within groups	284.760	444	0.643		
	Total	284.986	447			
A	Between groups	0.341	3	0.085	0.238	0.917
	Within groups	158.766	444	0.358		
	Total	159.107	447			
BI	Between groups	0.097	3	0.024	0.059	0.994
	Within groups	183.157	444	0.413		
	Total	183.254	447			

RQ7. Do the Scores Obtained from the Sub-Factors of TAM Scale Show a Significant Difference According to the Teaching Experience of STEM Teachers?

According to **Table 11**, TAM's sub-dimensions of self-efficacy towards using artificial intelligence applications ($F_{3\text{-}444} = 0.652$, $p > 0.05$), stress and anxiety ($F_{3\text{-}444} = 0.760$, $p > 0.05$), expected benefits ($F_{3\text{-}444} = 2.097$, $p > 0.05$), ease of use ($F_{3\text{-}444} = 0.088$, $p > 0.05$), attitude ($F_{3\text{-}444} = 0.238$, $p > 0.05$) and intention to use artificial intelligence applications ($F_{3\text{-}444} = 0.059$, $p > 0.05$) sub-dimensions do not show any difference according to teachers' years of teaching experience. Therefore, both a newly appointed teacher and a teacher with more than 20 years.

RQ8. Do the Scores Obtained from the Sub-Factors of TAM Scale Show a Significant Difference According to the Academic Levels of STEM Leachers?

According to **Table 12**, the scores obtained from TAM's sub-dimensions of self-efficacy towards using AI applications ($F_{2\text{-}445} = 7.472$, $p < 0.05$), attitude ($F_{2\text{-}445} = 3.438$, $p < 0.05$), and intention to use AI application tools ($F_{2\text{-}445} = 4.335$, $p < 0.05$) show a significant difference according to the academic levels of STEM teachers. TUKEY test was conducted to investigate which groups this difference was between. Accordingly, in the self-efficacy sub-dimension, STEM teachers with master's and doctorate levels consider themselves significantly more competent to use artificial intelligence tools than undergraduate level. The difference in the attitude sub-dimension is between graduate level teachers and undergraduate level teachers. As a matter of fact, teachers with master's degree have significantly higher attitudes towards artificial intelligence tools. Similarly, in the sub-dimension of behavioural intention to use artificial intelligence tools, the average scores of teachers with master's degree level were found to be significantly higher than those of teachers with bachelor's degree level.

Table 12. One-way ANOVA result examining the change in STEM teachers' scores in the sub-dimensions of TAM according to teachers' academic levels

		Sum of Squares	df	Mean Squares	F	Sig.
SE	Between groups	6.173	2	3.086	7.472	0.001
	Within groups	183.827	445	0.413		
	Total	190	447			
SA	Between groups	1.264	2	0.632	1.766	0.172
	Within groups	159.284	445	0.358		
	Total	160.549	447			
EB	Between groups	0.285	2	0.143	0.559	0.572
	Within groups	113.537	445	0.255		
	Total	113.822	447			
EU	Between groups	6.161	2	3.080	4.916	0.08
	Within groups	278.825	445	0.627		
	Total	284.986	447			
A	Between groups	2.421	2	1.211	3.438	0.033
	Within groups	156.686	445	0.352		
	Total	159.107	447			
BI	Between groups	3.502	2	1.751	4.335	0.014
	Within groups	179.752	445	0.404		
	Total	183.254	447			

CONCLUSION

The study highlights that STEM teachers in Turkey hold favorable attitudes towards the use of AI in education, recognizing its potential to enhance teaching and learning experiences. However, male teachers demonstrated higher levels of self-efficacy and found AI applications easier to use than their female counterparts, pointing to a gender gap in confidence and technological comfort. Despite these differences, teachers across various demographics-age, experience, and academic level-shared similar views on the potential benefits and usability of AI. This indicates that, while STEM educators are willing to adopt AI technologies, tailored support may be necessary to bridge the gender gap and ensure smooth integration of AI in classrooms.

RECOMMENDATIONS

To fully capitalize on the benefits of AI in STEM education, targeted professional development programs should be implemented to boost female teachers' confidence and technical proficiency with AI applications. These programs should focus on hands-on training and offer gender-sensitive approaches that address the specific challenges female educators may face. Additionally, schools should provide ongoing support to teachers, including technical resources and peer mentoring, to reduce stress and anxiety related to AI use. On the other hand, Future research should explore the long-term effects of AI integration on student outcomes and teachers' professional development, broadening the study to include other subject areas and regions for a more comprehensive understanding of AI adoption in education.

Additionally, the study primarily considered psychological and perceptual variables, such as self-efficacy, stress and anxiety, perceived usefulness, ease of use, attitude, and behavioral intention, within the framework of the Extended Technology Acceptance Model (TAM). While these factors offer valuable insights, the exclusion of external influences, such as social factors, institutional support, and infrastructure, may limit the scope of the findings. These elements could play a significant role in shaping teachers' acceptance and integration of Generative AI. Future research should expand the model to incorporate these external determinants, allowing for a more comprehensive understanding of the challenges and enablers of AI adoption in STEM and broader educational contexts.

STUDY LIMITATIONS

One limitation of the current study is that it focuses on STEM teachers. Therefore, generalization of the study findings to teacher groups with different backgrounds should be made with caution and future studies should include teachers with other backgrounds as well. The measures adopted in this study focus on existing variables, such as self-efficacy and anxiety. This however may limit the study's findings.

Moreover, the higher proportion of female participants (79.2%) in the study compared to male participants (20.8%), may influence the interpretation of gender-related findings. This limitation is acknowledged in the study, and future research should aim for a more balanced sample to enhance the representativeness of the results. Although the Stress and Anxiety factor was measured and the analysis was repeated with consistent results, its removal improved the model fit. This suggests the need for further exploration of its role in technology adoption, and future studies may benefit from revising the scale to enhance its reliability.

Author contributions: AAD: design, conceptualization, writing – original draft, writing – review & editing; NM: data curation, formal analysis, writing – original draft, writing – review & editing. All authors have agreed with the results and conclusions.

Funding: No funding source is reported for this study.

Ethical statement: The authors stated that the study did not require formal ethics approval. The study involved anonymized survey responses from science and mathematics teachers, with no sensitive personal data or interventions. The authors further stated that the highest ethical practices in scientific research were followed, including informed consent and data confidentiality.

Declaration of interest: No conflict of interest is declared by the authors.

Data sharing statement: Data supporting the findings and conclusions are available upon request from the corresponding author.

REFERENCES

Aburbeian, M., Owda, Y., & Owda, M. (2022). A technology acceptance model survey of the metaverse prospects. *AI, 3*(2), 285-302. https://doi.org/10.3390/ai3020018

Al Darayseh, A. (2023). Acceptance of artificial intelligence in teaching science: Science teachers' perspective. *Computers and Education: ArtificialIntelligence, 4*, Article 100132. https://doi.org/10.1016/j.caeai.2023.100132

AlKanaan, H. (2022). Awareness regarding the implication of artificial intelligence in science education among pre-service science teachers. *International Journal of Instruction*, *15*(3), Article 895912. https://doi.org/10.29333/iji.2022.15348a

Anderson, J. C., & Gerbing, D. W. (1984). The effect of sampling error on convergence, improper solutions, and goodness-of-fit indices for maximum likelihood confirmatory factor analysis. *Psychometrika, 49*(2), 155-173. https://doi.org/10.1007/BF02294170

Arbuckle, J. L. (2007). *AMOS 16.0*. Spring House, PA: Amos Development Corporation.

Asiri, M., & El aasar, S. (2022). Employing technology acceptance model to assess the reality of using augmented reality applications in teaching from teachers' point of view in Najran. *Journal of Positive School Psychology*, *6*(2), 5241-5255.

Baidoo-Anu, D., & Owusu Ansah, L. (2023). Education in the era of generative artificial intelligence (AI): Understanding the potential benefits of ChatGPT in promoting teaching and learning. *Journal of AI, 7*(1), 52-62. https://doi.org/10.61969/jai.1337500

Bhutoria, A. (2022). Personalized education and Artificial Intelligence in the United States, China, and India: A systematic review using a human-in-the-loop model. *Computers and Education: Artificial Intelligence, 3*, Article 100068. https://doi.org/10.1016/j.caeai.2022.100068

Brislin, R. W. (1980). Cross-cultural research methods. In I. Altman, A. Rapoport, & J. F. Wohlwill (Eds.), *Environment and Culture* (Vol. 4, pp. 47-82). Springer, Boston, MA. https://doi.org/10.1007/978-1-4899-0451-5_3

Byrne, B. M. (2010). *Structural equation modeling with AMOS: Basic concepts, applications, and programming* (2nd ed.). New York: Taylor and Francis Group, LLC.

Çam, H., & Günal, Z. (2016). Identifying the factors which is affecting the outsourcing of businesses wıth structural equation modeling. *Gümüshane University Electronic Journal of the Institute of Social Sciences, 7*(15), 210-229.

Çelik, M., &Turunç, Ö. (2011). Emotional labor and psychological distress: The mediating effect of work family conflict. *Istanbul University Journal of the School of Business Administration, 40*(2), 226-250.

Chan, R.C.H. (2022). A social cognitive perspective on gender disparities in self-efficacy, interest, and aspirations in science, technology, engineering, and mathematics (STEM): The influence of cultural and gender norms. *International Journal of STEM Education, 9*, Article 37. https://doi.org/10.1186/s40594-022-00352-0

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access, 8*, 75264-75278. https://doi.org/10.1109/ACCESS.2020.2988510

Cukurova, M., Khan-Galaria, M., Millán, E., & Luckin, R. (2021). A learning analytics approach to monitoring the quality of online one-to-one tutoring. *Journal of Learning Analytics*, *9*(2), 105-120. https://doi.org/10.35542/osf.io/qfh7z

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, *35*(8), 982-1002. https://doi.org/10.1287/mnsc.35.8.982

Durak, H. (2019). Examining the acceptance and use of online social networks by preservice teachers within the context of unified theory of acceptance and use of technology model. *Journal of Computing in Higher Education*, *31*(1), 173-209. https://doi.org/10.1007/s12528-018-9200-6

Frias, C. M., & Dixon, R. A. (2005). Confirmatory factor structure and measurement invariance of the memory compensation questionnaire. *Psychological Assessment, 17*(2), 168-178. https://doi.org/10.1037/1040-3590.17.2.168

Grassini, S. (2023). Shaping the future of education: Exploring the potential and consequences of AI and ChatGPT in educational settings. *Education Sciences, 13*, Article 692. https://doi.org/10.3390/educsci13070692

Guner, H., & Acarturk, C. (2020). The use and acceptance of ICT by senior citizens: A comparison of technology acceptance model (TAM) for elderly and young adults. *Universal Access in the Information Society*, *19*(2), 311-330. https://doi.org/10.1007/s10209-018-0642-4

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., & Thiele, K. O. (2017). Mirror, mirror on the wall: A comparative evaluation of composite-based structural equation modeling methods. *Journal of the Academy of Marketing Science*, *45*, 616-632. https://doi.org/10.1007/s11747-017-0517-x

Harrington, D. (2009). *Confirmatory factor analysis*. Oxford university press. https://doi.org/10.1093/acprof:oso/9780195339888.001.0001

Hébert, C., Jenson, J., & Terzopoulos, T. (2021). "Access to technology is the major challenge": Teacher perspectives on barriers to DGBL in K-12 classrooms. *E-Learning and Digital Media, 18*(3), 307-324. https://doi.org/10.1177/2042753021995315

Hu, L., & Bentler, P. (2000). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1-55. https://doi.org/10.1080/10705519909540118

Jöreskog, K. G., & Sörbom, D. (1993). *LISREL 8: Structural equation modeling with the SIMPLIS command language*. Scientific Software International.

Kao, C. P., & Tsai, C. C. (2009). Teachers' attitudes toward web-based professional development, with relation to Internet self-efficacy and beliefs about web-based learning. *Computers & Education, 53*(1), 66-73. https://doi.org/10.1016/j.compedu.2008.12.019

Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., ... Kasneci, G. (2023). ChatGPT for good? Onopportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, Article 102274. https://doi.org/10.1016/j.lindif.2023.102274

Kim, N., & Kim M. (2022). Teacher's perceptions of using an artificial intelligence-based educational tool for scientific writing. *Frontiers in Education*, *7*, Article 755914. https://doi.org/10.3389/feduc.2022.755914

Kline, R. B. (1998). *Principles and practice of structural equation modeling*. New York: Guilford.

Kok, J. N., Boers, E. J., Kosters, W. A., van der Putten, P., & Poel, M. (2009). Artificial intelligence: Definition, trends, techniques, and cases. *Knowledge for sustainable development: An insight into the encyclopedia of life support systems* (pp. 1095-1107). Eolss Publishers.

Lee, U., Han, A., Lee, J., Kim, J., Kim, H., & Lim, C. (2023). Prompt aloud!: Incorporating image-generative AI into STEAM class with learning analytics using prompt data. *Education and Information Technologies*, *29*, 9575-6905. https://doi.org/10.1007/s10639-023-12150-4

Lew, S. L., Lau, S. H., & Leow, M. C. (2019). Usability factors predicting continuance of intention to use cloud e-learning application. *Heliyon*, *5*(6), 1-11. https://doi.org/10.1016/j.heliyon.2019.e01788

Lindner, A., & Romeike, R. (2019). Teachers' perspectives on artificial intelligence. In *12th International Conference on Informatics in Schools*. *Situation, evaluation and perspectives.* Larnaca, Cyprus. https://www.researchgate.net/publication/337716601

Marcoulides, G., & Schumacher, R. (2001). *New developments and techniques in structural equation modelling*. London: Lawrence Erlbaum Associates Publishers. https://doi.org/10.4324/9781410601858

Marsh, H. W., Balla, J. R., & McDonald, R. P. (1988). Goodness-of-fit indexes in confirmatory factory analysis: The effects of sample size. *Psychological Bulletin, 103*(3), 391-410. https://doi.org/10.1037/0033-2909.103.3.391

Nikitas, A., Michalakopoulou, K., Njoya, E., & Karampatzakis, D. (2020). Artificial intelligence, transport and the smart city: Definitions and dimensions of a new mobility era. *Sustainability MDPI Journal*, *12*(7), 1-19. https://doi.org/10.3390/su12072789

Qadir, J. (2022). *Engineering education in the era of Chatgpt: Promise and pitfalls of generative aIfor education*. TechRxiv. https://doi.org/10.36227/techrxiv.21789434.v1

Saade, R., Nebebe, F., & Tan, W. (2007). Viability of the "technology acceptance model" in multimedia learning environments: A comparative study. *Journal of eLearning and Learning Objects*, *3*, 175-184. https://doi.org/10.28945/392

Sánchez-Prieto, J. C., Olmos-Migueláñez, S., & García-Peñalvo, F. J. (2016). Informal tools in formal contexts: Development of a model to assess the acceptance of mobile technologies among teachers. *Computers in Human Behavior, 55*, 519-528.

Schermelleh-Engel, K., Moosbrugger, H., & Müller, H. (2003). Evaluating the fit of structural equation models: Tests of significance and descriptive goodness-of-fit measures. *Methods of Psychological Research Online, 8*(2), 23-74.

Schumaker, R., & Lomax, R. (2004). *A beginner's guide to structural equation modeling* (2nd ed.). Mahwah, NJ: Psychology Press. https://doi.org/10.4324/9781410610904

Shin, S., & Shin, H. (2020). A study on the application of artificial intelligence in elementary science education. *Journal of Korean Elementary Science Education, 39*(1), 117-132. https://doi.org/10.15267/KESES.2020.39.1.117

Şimşek, Ö. F. (2007). *Yapısal Eşitlik Modellemesine Giriş: Temel İlkeler ve Lisrel Uygulamalari* [Introduction to structural equation modeling: Basic principles and LISREL applications]. Ekinoks, Ankara.

Stone, P., Brooks, R., Brynjolfsson, E., Calo, R., Etzioni, O., Hager, G., Hirschberg, J., Kalyanakrishnan, S., Kamar, E., Kraus, S., Leyton-Brown, K., Parkes, D., Press, W., Saxenian, A. A., Shah, J., Tambe, M., & Teller, A. (2016). Artificial intelligence and life in 2030. In *Proceedings of the One-Hundred-Year Study on Artificial Intelligence: Report of the 2015-2016*. Stanford, CA: Stanford University.

Sümer, N. (2000). Yapısal Eşitlik Modelleri: Temel kavramlar ve örnek uygulamalar [Structural equation models: Basic concepts and example applications]. *Türk Psikoloji Yazıları*, *3*(6), 74-79.

Tallvid, M. (2016). Understanding teachers' reluctance to the pedagogical use of ICT in the 1:1 classroom. *Education and Information Technologies, 21*(3), 503-519. https://doi.org/10.1007/s10639- 014-9335-7

Tanaka, J. S., & Huba, G. J. (1985). A fit index for covariance structure models under arbitrary GLS estimation. *British Journal of Mathematical and Statistical Psychology, 38*(2), 197-201. https://doi.org/10.1111/j.2044-8317.1985.tb00834.x

Teo, T. (2019). Students and teachers' intention to use technology: Assessing their measurement equivalence and structural invariance. *Journal of Educational Computing Research, 57*(1), 201-225.

Topal, A. D., Eren, C. D., and Geçer, A. K. (2021). Chatbot application in a 5th grade science course. *Education and Information Technologies, 26*(5), 6241-6265. https://doi.org/10.1007/s10639- 021-10627-8

United Nations Educational, Scientific and Cultural Organization [UNESCO]. (2019). *The challenge and opportunities of artificial intelligence in education*. Paris: The United Nations Educational, Scientific and Cultural Organization.

Ursavaş, Ö. F., Yalçın, Y., & Bakır, E. (2019). The effect of subjective norms on preservice and in-service teachers' behavioural intentions to use technology: A multigroup multimodel study. *British Journal of Educational Technology, 50*(5), 2501-2519.

Wang, Y., Liu, C., & Tu, Y.-F. (2021). Factors affecting the adoption of AI-based applications in higher education: An analysis of teachers perspectives using structural equation modeling. *Educational Technology & Society, 24*(3), 116-129. https://www.jstor.org/stable/27032860

Wang, W. T., & Wang, C. C. (2009). An empirical study of instructor adoption of web-based learning systems. *Computers & Education, 53*(3), 761-774. https://doi.org/10.1016/j.compedu.2009.02.021

Yılmaz, V., & ve Çelik, H. E. (2009). *Lisrel ile yapısal eşitlik modellemesi-1* [Structural equation modeling with LISREL-1]. Ankara: Pegem Yayıncılık.

Zhao, L., Chen, L., Liu, Q., Zhang, M., & Copland, H. (2019). Artificial intelligence-based platform for online teaching management systems. *Journal of Intelligent & Fuzzy Systems, 37*(1), 45-51.