Journal of Studies in Education
ISSN 2162-6952
2025, Vol. 15, No. 4

Exploring Math Teachers' Artificial Intelligence Self-Efficacy (TAISE)

Masooma Ali Al-Mutawah (Corresponding author)

Chair of Math, Science and ICT Department, Bahrain Teachers College

University of Bahrain, P.O. Box 32038, Zallaq, Kingdom of Bahrain

Tel: 973-1743-8970 E-mail: malmutawah@uob.edu.bh

Received: July 1, 2025 Accepted: August 20 2025 Published: November 1, 2025

doi:10.5296/jse.v15i4.23009 URL: https://doi.org/10.5296/jse.v15i4.23009

Abstract

In the rapidly changing technological landscape of today, teachers' ability to use AI effectively is becoming more and more important for facilitating successful pedagogical practices and incorporating technology into the classroom. One important aspect affecting teachers' performance, motivation, and eventually their students' academic success is their Artificial Intelligence Self-Efficacy (TAISE). TAISE is still largely unexplored despite its importance. This study examines the AI self-efficacy of 280 mathematics teachers in Bahrain and how their self-efficacy in four areas- assistance, anthropomorphic interaction, comfort with AI, and technological skills- is influenced by their gender, age, and academic background. The TAISE scale's psychometric validation using exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) revealed great structural integrity and outstanding reliability. The findings showed a generally high level of self-efficacy in all domains, with anthropomorphic interaction showing a slight gender preference for females. In every self-efficacy characteristic, teachers with 6-10 years of experience outperformed their more seasoned peers. Furthermore, teachers between the ages of 20 and 30 showed greater technological proficiency and comfort using AI tools. These observations highlight how crucial it is to provide specialized training for professionals that improves technological proficiency while taking experience and generational differences into consideration.

Keywords: Artificial Intelligence AI; Artificial Intelligence in Education AIED; Teacher Artificial Intelligence Self-efficacy TAISE; Math Education.

1. Introduction

In Given the difficulty in identifying clear, observable characteristics that reliably predict teacher effectiveness, researchers have increasingly turned their attention to less tangible psychological factors. Among these, teacher self-efficacy has emerged as one of the most extensively studied constructs in the literature (Jerrim et al., 2023).

The concept of self-efficacy reflects teachers' confidence in their abilities and the value they bring to their profession, representing a cognitive process that also encompasses emotional states (Achurra & Villardón, 2012; Demir, 2021). Teacher self-efficacy specifically refers to an educator's belief in their capacity to successfully carry out teaching-related tasks, such as integrating technology, and achieve desired educational outcomes, demonstrating confidence in their ability to teach effectively (Gordon et al., 2023). In adapting teaching practices to meet the demands of a rapidly changing educational landscape, self-efficacy beliefs play a pivotal role. These beliefs influence how teachers select instructional activities, organize lessons, integrate technology, and approach challenging situations (Bandura, 1997). According to social cognitive theory, teachers' belief in their ability to manage and deliver high-quality instruction is a critical determinant of their teaching practices. Such beliefs also enable educators to reflect on and better understand their attitudes toward their professional competence (Woodcock & Hardy, 2023).

Research has shown that educators with high levels of self-efficacy are more receptive to innovative ideas and adopt a proactive approach in exploring contemporary teaching strategies, particularly those involving technology to improve student outcomes (Channawar, 2023). A strong sense of self-efficacy contributes significantly to human achievement and well-being. Individuals confident in their abilities tend to approach challenging tasks with motivation and resilience, rather than fear or discouragement. This positive mindset fosters intrinsic motivation and enables them to engage more deeply and persistently in an innovative teaching strategies and educational professional responsibilities (Shah, 2023).

The integration of artificial intelligence (AI) tools in education has significantly transformed learning experiences and outcomes. As educators navigate the challenge of balancing instructional support with fostering self-directed learning, they require a strong sense of self-efficacy to adapt to and effectively engage with this evolving landscape (Bilad et al., 2023). Research indicates that the role of artificial intelligence in education (AIED) is to enhance learning effectiveness and support the delivery of more efficient and intelligent educational activities (Fitria, 2023). Teaching approaches have evolved significantly with the advancement of AI technologies, leading to faster and more dynamic interactions between students and internet-based systems. This shift requires teachers to develop both the confidence and competence to effectively integrate AI into educational practices (AlKanaan, 2022).

Assessing teachers' AI self-efficacy (TAISE) and attitudes within educational settings is vital for informing the design of targeted professional development programs and fostering inclusive environments that address the diverse needs of all learners especially in the era of artificial intelligence (Opingo & Linox, 2024). Embedding self-efficacy principles into professional development frameworks is equally critical, as strengthening teachers' confidence and competence has been shown to positively influence instructional quality and, consequently, student achievement (Bray-Clark & Bates, 2003).

1.1 Research Aims and Questions

The primary objective of this study is to examine the Artificial Intelligence self-efficacy of math teachers. The focus is on understanding their proficiency in grasping the implications of AI and its practical applications, encompassing their AI readiness and knowledge. By scrutinizing their AI self-efficacy, the study aims to highlight areas of growth and opportunity in teachers' pedagogical practices, supporting them in acquiring the skills needed to confidently integrate AI tools and technologies into their teaching. The insights derived from this investigation can inform the ongoing development of teacher professional learning programs, inspire context-responsive initiatives, and enrich curricula to foster AI self-efficacy among educators. Ultimately, the purpose of this study is to investigate math teachers' acceptance of AI products and technology as well as their level TAISE to bolster the integration of AI in math education, thereby augmenting student learning outcomes.

Therefore, the research questions of the study are:

1- Is the TAISA questionnaire valid and reliable when used with mathematics teachers in Bahrain?

2- How will math teachers' self-efficacy 4 domain (Assistance, Anthropomorphic Interaction, Comfort with AI, Technological Skills) affect their successful use of AI in the classroom?

3- How do factors such as gender, age, years of experience, and academic level influence the AI self-efficacy of mathematics educators?

It is anticipated that the results of this study will provide insight into the professional development programs required for math teachers, to improve their ability to apply AI.

2. Literature Review

2.1 Artificial Intelligence Self-Efficacy

While teachers' confidence in their self-efficacy significantly influences the quality of their teaching, it also shapes their instructional methods, classroom techniques, student engagement, and learners' comprehension—making it a key determinant of student success (Er, 2020). At the same time, the future of society depends on fostering informed perspectives about AI and developing AI-related skills, a challenge with profound implications for K-12 education (Antonenko & Abramowitz, 2023). Research further suggests that high levels of teacher self-efficacy are linked to improved participation across academic domains and the development of diverse skills and abilities (Bhati & Sethy, 2022). Moreover, several studies have found strong connections between teachers' classroom management practices and their self-efficacy beliefs (Berger et al., 2018). Rahman et al. (2022) investigated the relationship between teachers' knowledge of Technological Pedagogical Content Knowledge (TPACK) and their self-efficacy, by analyzing thirty-four high-quality studies, they provided empirical insights into this connection. The results indicated that teachers' self-efficacy is strongly influenced by their TPACK, especially in educational contexts where technology is extensively integrated.

Oran (2023) identified a research gap regarding the relationship between AI literacy and teacher self-efficacy through a comprehensive literature review. The implications of his study emphasized the importance for educators to leverage AI to enhance work efficiency rather than relying solely on the technology.

In a study for Arnado et al. (2022), purposely selected seventy-one STEM teachers of Agusan del Norte Division the results showed significant relationship between the STEM teachers' laboratory self-efficacy beliefs to their respective STEM teaching attitudes and science teaching efficacy beliefs showing a low positive correlation. The study recommended that self-efficacy perception enhancing activities should be intensified in teachers' training.

Focusing on psychological aspects, Parsakia (2023) conducted a thorough literature review study and found that frequent and satisfying interactions with AI applications like chatbots can enhance TAISE and engagement.

Chou et al. (2023) conducted a study to create a 'Teachers' Efficacy Perceptions of AI-based Teaching Applications scale', researchers analyzed how six factors related to AI impacted 714 vocational senior high school teachers in Taiwan. The research explored how teachers' backgrounds, including gender, position, school attributes, seniority, and AI teaching experience, influenced their perceived efficacy in AI-based teaching. The results could guide educational units in promoting the use of AI technology in teaching and training.

The relationship between teaching experience and self-efficacy remains inconclusive. While large-scale studies often report weak or nonsignificant correlations between years of teaching experience and self-efficacy, findings from longitudinal research suggest otherwise, indicating that teachers with greater experience tend to report higher levels of self-efficacy (Gale et al., 2021).

This study aims to investigate mathematics teachers' Artificial Intelligence Self-Efficacy (TAISE), which comprises four distinct components: (1) an assistance factor, reflecting dimensions of the robot use self-efficacy scale (i.e., use of AI as a technological assistive tool); (2) - (3) two factors unique to the TAISE construct (i.e., anthropomorphic interaction and comfort with AI), and (4) a technological skills factor, aligned with dimensions of the computer self-efficacy scale (i.e., basic computer skills).

2.2 Assistance of AI Technologies/products

Research indicates that integrating artificial intelligence (AI) into education can personalize learning, provide more effective learning experiences, help students, foster creativity, and reduce teachers' workloads. However, to fully realize these advantages, it is essential to develop a teacher profile that effectively collaborates with AI-assisted systems (Gocen & Aydemir, 2020).

According to Henson (2001), teachers' self-efficacy is shaped by their simultaneous evaluation of the teaching task's challenges and available resources, along with their assessment of personal skills, knowledge, and traits. Together, these determine their confidence in teaching effectively. Individuals' beliefs about how technology can enhance their work performance, the perceived ease of acquiring the skills needed to use it effectively, and factors such as institutional support, access to technology, and the voluntary nature of adoption all play a critical role in shaping their acceptance of AI-assisted support (Galindo-Domínguez et al., 2024).

Research shows that AI technologies have been utilized in various educational domains including grading and feedback systems, virtual and assistant teachers, personalized and adaptive learning, augmented and virtual reality, and distance learning (Yufeia et al., 2020). Therefore, when teachers gain the confidence and acceptance to incorporate AI into these areas, it has the potential to greatly enhance their teaching effectiveness, ultimately resulting in better student outcomes.

In this study's questionnaire, teachers were asked about their perceptions of using AI as an educational assistant, such as whether it makes learning easier, more engaging, saves time, and produces effective teaching aids. This aimed to examine the *Assistance* domain of their TAISE and its correlation with their ability to integrate AI successfully in the classroom.

2.3 Anthropomorphic Interaction with AI

Anthropomorphic AI, which imbues artificial intelligence with human-like traits, is increasingly becoming a topic of interest in research and development due to its potential impact on human-AI interaction (Placani, 2024). Anthropomorphism involves designing chatbots with human-like qualities, such as personality, emotions, and language. By enabling chatbots to interact in increasingly realistic ways, anthropomorphism helps users feel more at ease, as they attribute human-like characteristics to AI. This design strategy has been shown to positively influence digital interactions by enhancing user experience, trust, satisfaction, and attitudes toward the chatbot (Gomes et al., 2025).

Anthropomorphic AI reflective assistants hold considerable potential to transform reflective practices in education. By delivering interactive, emotionally engaging, and adaptive feedback, these tools can streamline the reflective process, foster self-directed learning, and enhance critical thinking and self-awareness (Bate & Eberhard, 2024). However, most existing research models tend to differentiate only between high and low levels of anthropomorphism, without exploring in depth whether specific types of anthropomorphism might be more effective in maximizing these outcomes. Furthermore, while prior studies have focused on how users perceive anthropomorphized characters, little attention has been given to how users relate to these agents in terms of their self-concept and identity (Alabed et al., 2022).

In the context of anthropomorphic interaction, verbal persuasion -such as positive feedback and encouragement from human-like AI agents- can play a significant role in shaping users' self-efficacy. By leveraging social cues and emotional expressions, these agents have the potential to enhance individuals' confidence in their abilities and promote greater engagement and persistence in tasks (Hussain & Khan, 2022). However, while verbal persuasion alone has a limited impact on enhancing teacher self-efficacy, it can provide supportive encouragement during challenging situations and help mitigate the adverse effects of self-doubt (Bandura, 1997). Research on teacher self-efficacy further suggests that verbal persuasion becomes a less significant predictor for experienced educators, whose self-efficacy increasingly relies on accumulated mastery experiences rather than external encouragement (Lazarides & Warner, 2020).

In this study's questionnaire, teachers were asked about their anthropomorphic interaction with AI, including whether they felt as if they were chatting or interacting with a real person. This aimed to explore the Anthropomorphic Interaction domain of their TAISE and its correlation with their ability to use AI effectively in the classroom.

2.4 Comfort and Ease with AI

AI holds significant potential to provide comfort and address teacher anxiety through personalized interactions and predictive solutions. By enhancing the efficiency and responsiveness of support systems, AI-driven tools can boost teachers' confidence and alleviate anxiety through high-quality service and tailored recommendations (Al-Hadrawi et al., 2025)

Teachers with cross-disciplinary expertise and reflective training are more confident and comfortable using AI in education, as their diverse skills enable them to integrate technology with greater ease. Their ability to navigate complex, technology-enhanced learning environments with ease underscores the importance of broad expertise and reflective practice in preparing educators for AI integration (Chou et al., 2023).

Parsakia (2023) reviewed the impact of AI tools on self-efficacy in health behaviors, highlighting how supportive interactions with chatbots can reduce stress and promote user comfort, thereby indirectly enhancing self-efficacy in controlled settings. This aligns with Sapna's (2017) observation that negative self-perceptions and anxiety often undermine performance, suggesting that emotionally responsive AI tools may help mitigate these effects. Notably, self-efficacy is also closely linked to critical dimensions of teachers' psychological well-being; educators with strong confidence in their abilities report higher job satisfaction, greater professional commitment, and a lower risk of burnout (Gale et al., 2021). These findings underscore the potential of AI tools to foster a sense of ease and confidence in teachers, supporting not only their performance but also their self-efficacy.

In this study's questionnaire, teachers were asked about their comfort with AI through items assessing whether they felt calm, peaceful, and relaxed when interacting with it. This explored the Comfort with AI domain of their TAISE and how emotional ease with AI might influence their successful classroom integration of such technologies.

2.5 AI Technological Skills

Assessing teachers' AI competence and fostering effective, safe, and supportive learning environments are essential for a successful transition to AI-integrated education (Chiu et al., 2024). Such efforts can empower teachers to perform their roles with greater confidence and efficacy.

Oran (2023) underscores the significance of teachers acquiring proficiency in the use of AI tools such as ChatGPT. This expertise encompasses a deep understanding of the AI tool's features, its operational mechanics, and the skill to craft engaging prompts for interaction. Educators should also be ready to address any challenges that emerge during integration and remain current with updates and advancements to maximize the tool's effectiveness in educational environments.

Individual emotional states such as anxiety, stress, worry, and fear of failure significantly influence self-efficacy. Experiencing stress or fear can negatively impact a person's belief in their abilities. Anxiety, in particular, triggers emotional arousal that can reduce self-efficacy (Hussain & Khan 2022). To strengthen teachers' self-efficacy, it is essential to reduce stress and negative emotional arousal. Additionally, teachers should be supported in recognizing that physiological and emotional responses, such as anxiety, are not signs of weakness or incompetence (Lazarides & Warner, 2020). As teachers' confidence in their technical competence to adapt to student-centered approaches is crucial for effective educational practices (Shah, 2023).

In this study's questionnaire, teachers were asked about their technological skills, including whether they feel anxious when pressing the wrong button or encountering technical jargon they do not understand. This examined the Technological Skills domain of their TAISE and how their confidence in handling technology may influence their readiness to use AI in teaching practices.

3. Methodology

3.1 Participants and Sample Size

The research study encompassed 280 math teachers selected through random sampling to minimize bias and enhance the generalizability of the findings. The sample was thoughtfully curated from diverse locations across Bahrain, spanning Primary, Intermediate, and High government schools. This selection ensured a wide representation of educators, including both male and female teachers with varied teaching experiences, ages, and demographic profiles, thus creating a comprehensive and inclusive sample. Teachers were provided with a Google Form containing survey questions and were allocated one month to complete their responses. Throughout this period, participants were assured of the confidentiality of their answers, with a commitment that the data would be utilized solely for research purposes aimed at advancing AI practices in education. Upholding ethical standards and maintaining transparent communication regarding participant information were fundamental in fostering trust and collaboration among the teachers involved in the study.

3.2 Instrument

The survey used in this research is sourced from a reputable origin with established reliability and validity for assessing participants' Artificial Intelligence Self-Efficacy concerning the use of AI technologies and products (Wang & Chuang, 2024). This 22-item tool is designed to cover a wide range of asynchronous AI technologies and products, providing a general framework for comparative analysis. The TAISE scale can also function as a self-assessment tool for AI knowledge and skills learning and performance. It is divided into four key dimensions: Assistance (7 items), Anthropomorphic interaction (5 items), Comfort with AI (6 items), and Technological skills (4 items). All items impacting teachers' effective use of AI in the classroom. Utilizing a Likert scale, participants are asked to indicate their level of agreement or disagreement with statements on a five-point scale, ranging as 1: strongly disagree, 2: disagree, 3: neutral, 4. agree and 5. strongly agree.To verify the structure of the elements and to guarantee the validity and reliability of the questionnaire, EFA and CFA will be conducted. Table 1 shows the survey items.

Table 1. Teacher's Artificial Intelligence Self-Efficacy (22-Item)

Scale		Items
Assistance	AS1	Some AI technologies/products make learning easier.
	AS2	I find that AI technologies/products are helpful for learning.
	AS3	AI technologies/products are good aids to learning.
	AS4	Using AI technologies/products makes learning more interesting.
	AS5	I'm confident in my ability to learn simple programming of AI technologies/products if I were provided the necessary training.
	AS6	AI technologies/products help me to save a lot of time.
	AS7	I find it easy to get AI technologies/products to do what I want it to do.
Anthropomorphic Interaction	AI1	I think the interactive process of AI technologies/products is very vivid, just like chatting with a real person.
	AI2	I think the way that AI technologies/products express content when interacting is unique, just like a real person.

	AI3	I think there is no difference between the dialogue method of AI technologies/products compared with the dialogue with real people.
	AI4	I think the tone of AI technologies/products when interacting is the same as that of real people.
	AI5	I feel that the way of expression of AI technologies/products in the interactive text is the same as that of real people.
Comfort with AI	CF1	When interacting with AI technologies/products, I feel very calm.
	CF2	When interacting with AI technologies/products, I find it easy.
	CF3	When interacting with AI technologies/products, I feel comfortable in my heart.
	CF4	When interacting with AI technologies/products, I feel very peaceful.
	CF5	When interacting with AI technologies/products, I feel very relaxed.
	CF6	I can happily interact with AI technologies/products smoothly.
Technological skills	TS1	When using AI technologies/products I am not worried that I might press the wrong button and cause risks.
	TS2	When using AI technologies/products I am not worried that I might press the wrong button and damage it.
	TS3	When using an AI technology/product, there is nothing that I do not know why.
	TS4	AI technologies/products jargon does not baffle me.

3.3 Research model

The research model for this study is shown in Figure 1, in this model we are testing how Teachers' self-efficacy influences teachers' responses to questions concerning four dimensions.

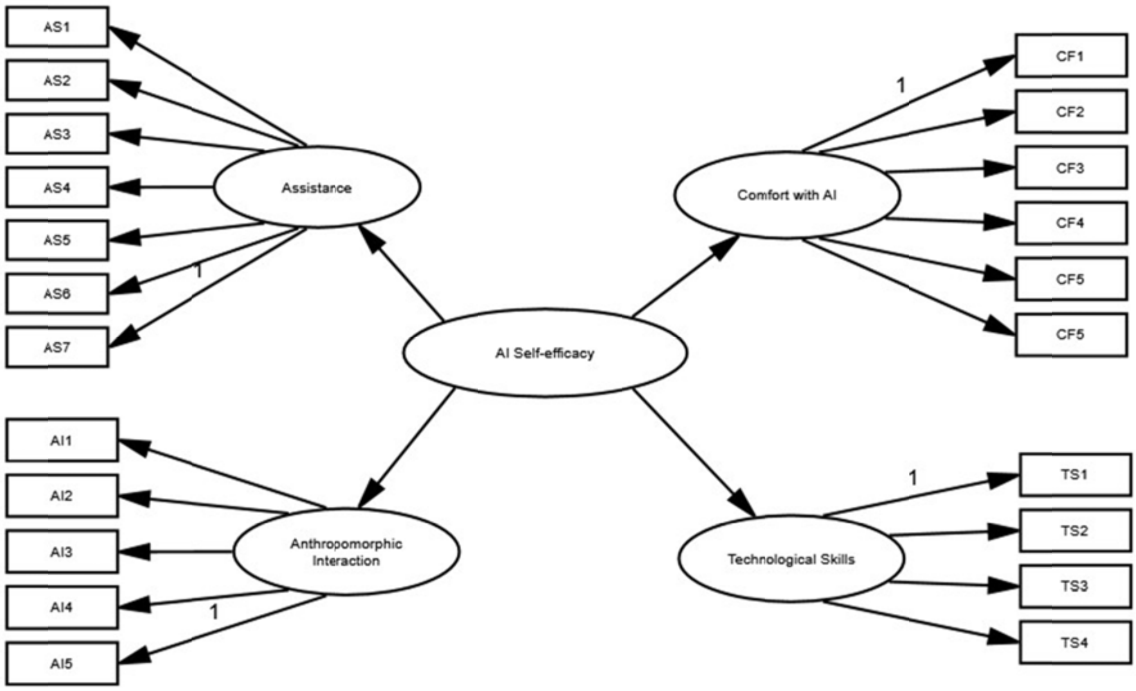

Figure 1. *Research model.*

4. Results and Discussion

4.1 Data Analysis

First, the data was examined for anomalies and missing responses. The dimensionality of the artificial intelligence self-efficacy constructs was investigated using exploratory factor analysis (EFA). The validity and reliability of the scale were tested through the confirmatory factor analysis method (CFA) (Harrington, 2009) by using the partial least squares structural equation modelling (PLS-SEM) method. The assessment of the reliability of the scale was reported by the composite reliability (CR) and outer loading values. Meanwhile, convergent validity for this scale was assessed through the average variance extracted (AVE) values. In the current study, discriminant validity was determined through the HTMT criterion. Table 2 summarizes the acceptance criterion for the reported values of the validity and reliability of the scale.

Table 2. Acceptance criteria of reliability and validity for reflective measurement model assessments in PLS-SEM

Categories	Indexes	Assumptions	References
Internal consistency reliability	Composite reliability (CR)	CR < 0.6 (low)	Hair et al. (2014)
		CR: 0.7–0.9 (satisfied)	Nunnally & Bernstein (1994)
		CR: 0.6–0.7 (Acceptable for exploratory research)	Hair et al. (2014)
		CR > 0.90	Hair et al. (2014)
Indicator reliability	Outer loading	Outer loading > 0.7 (suggested)	Hair et al. (2010)
		$0.4 \leq \mathit{outer\ loading} < 0.7$ (Acceptable with certain conditions)	Hulland (1999) Byrne (2016)
		Outer loading < 0.4 (should be eliminated)	Bagozzi et al. (1991) Hair et al. (2011)
Convergent validity	Average variance extracted (AVE)	AVE > 0.50	Hair et al. (2017) Bagozzi et al. (1991) Fornell & Larcker (1981)
Discriminant validity	HTMT criterion	HTMT	Kline (2016) Dzin & Lay (2021)

Statistical analyses based on gender, years of experience, and academic level were conducted using t-tests and one-way ANOVA to determine significant differences in the construct of AI self-efficacy of mathematics educators. The demographic background of the study sample is identified in Table 3.

Table 3. Demographic background of the study sample (n=280)

	Demographic	Frequency	Percent
Gender	Male	134	47.9%
	Female	146	52.1%
Age	20-30	88	31.4%
	31-40	87	31.1%
	41-50	64	22.9%
	51+	41	14.6%
Teaching experience	5 years or less	91	32.5%
	6-10 years	52	18.6%
	11 years and above	137	48.9%
Teaching level	Primary School	117	41.8%
	Middle School	102	36.4%
	High School	61	21.8%
Academic level	Bachelor’s	230	82.2%
	Higher Diploma	37	13.2%
	Master’s/Phd	13	4.6%

4.2 Descriptive Statistics

The normality assumption was examined using the mean, standard deviation, skewness, and kurtosis for each construct, as shown in Table 4. Participants' responses were distributed near the mean, as evidenced by mean scores that ranged from 3.44 to 4.06 and no standard deviation that was more than 1.00. Kurtosis varied from -0.318 to 1.832, while skewness ranged from

-0.673 to 0.044. The data satisfied the multivariate normal distribution assumption of the data structural equation modeling, as indicated by the absolute skewness and kurtosis values in Table 4 being less than 3 and less than 10, respectively (Kline, 2016).

Table 4: Descriptive statistics for the scales in AI self-efficacy.

Scale	Mean	SD	Skewness	Kurtosis
Assistance (AS)	4.06	0.62	-0.67	1.83
Anthropomorphic interaction (AI)	3.51	0.82	-0.21	-0.14
Comfort with AI (CF)	3.51	0.81	-0.09	-0.32
Technological skills (TS)	3.44	0.83	0.04	-0.09

4.3 Exploratory factor analysis

The validity of the 22 questions measuring AI self-efficacy (assistance, anthropomorphic interaction, comfort with AI, and technological skills) was investigated using principal axis factoring with varimax rotation. The constructs' Kaiser-Meyer-Olkin (KMO) index was 0.926, over the suggested threshold of 0.60 (Kaiser, 1974). Because Bartlett's test of sphericity was statistically significant, the correlation matrix's factorability was validated. As a result, factor analysis was deemed appropriate for the data.

One item from Anthropomorphic Interaction (AI1) and two items from Comfort with AI (CF6, CF2) were removed from further analysis because they did not satisfy the basic condition of having a factor loading of at least 0.40 on their respective scales. A total of 74.074% of the variance was explained by the remaining 19 items. The Cronbach's alpha and McDonald's omega reliability coefficients for each latent construct are listed in Table 5, along with the factor loadings for each item. The factor loading of the remaining 19 items was greater than .50 on its scale. For AS, Cronbach's alpha and McDonald's omega reliability coefficient were .901 and .902, respectively; for AI, Cronbach's alpha and McDonald's omega reliability coefficient were .871 and .877, respectively; while for CF, they were .932 and .939, respectively; and for TS, Cronbach's alpha and McDonald's omega reliability coefficient were .885 and .886, respectively.

Table 5. Factor loadings, percentage of variance, eigenvalue, and internal consistency reliability for two latent constructs

Item	Factor loading			
	Assistance	Anthropomorphic interaction	Comfort with AI	Technological skills
AS1	.848			
AS2	.871			
AS3	.841			
AS4	.704			
AS5	.587			
AS6	.747			
AS7	.532			
AI2		.506		
AI3		.783		
AI4		.748		
AI5		.775		
CF1			.584	
CF3			.797	
CF4			.750	
CF5			.615	
TS1				.799
TS2				.786
TS3				.650

TS4				.674
% Variance	46.713	15.031	7.620	4.709
Eigenvalue	8.876	2.856	1.448	0.895
Cronbach alpha reliability	.901	.871	.932	.885
McDonald's omega reliability	.902	.877	.939	.886

Factor loadings smaller than .40 have been omitted.

Items CF2, CF6, and AI1 were removed from all further analysis.

4.4 Assessment of the measurement model

Indicator loadings were used to analyze structures with reflective statements. Because they show that the idea explains more than 50% of the indicator's variance, resulting in adequate item reliability, Hair et al. (2019) suggest indicator loadings larger than 0.708. Table 6 shows that the outer loading value of each indicator is more than 0.708.

Internal consistency reliability was assessed using Joreskog's (1971) composite reliability (ρC). According to Hair et al. (2019), reliability scores between 0.60 and 0.70 are deemed "acceptable in exploratory research," whereas values between 0.70 and 0.90 are categorized as "satisfactory to good."

Journal of Studies in Education
ISSN 2162-6952
2025, Vol. 15, No. 4

Table 6. Establishing the measuring model's parameters

Construct	Items	loadings of factors	Cronbach's alpha	Reliability coefficient (rho_a)	Composite reliability (rho_c)	AVE
Assistance	AS1	0.891	0.910	0.917	0.931	0.695
	AS2	0.899				
	AS3	0.888				
	AS4	0.736				
	AS6	0.851				
	AS7	0.714				
Anthropomorphic Interaction	AI2	0.846	0.873	0.877	.907	0.662
	AI3	0.809				
	AI4	0.790				
	AI5	0.840				
Comfort with AI	CF1	0.848	0.932	0.933	0.947	0.749
	CF3	0.920				
	CF4	0.923				
	CF5	0.887				
Technological skills	TS1	0.865	0.886	0.889	0.921	0.744
	TS2	0.888				
	TS3	0.845				
	TS4	0.852				

Journal of Studies in Education
ISSN 2162-6952
2025, Vol. 15, No. 4

Despite using similar criteria, Cronbach's alpha performs worse than composite reliability as a measure of internal consistency (Hair et al., 2019). Furthermore, to give a precise and reliable substitute, a unique reliability coefficient ρA based on Dijkstra and Henseler (2015) was employed.

The convergent validity of each notion was examined in the following phase of the reflective measurement method. The convergent validity of the construct was assessed using the average variance extracted (AVE). A construct is considered acceptable, according to Hair et al. (2019), if its AVE is 0.50 or greater, meaning it accounts for at least 50% of the variance of the indicators that comprise the construct (Hair et al., 2022). Reliability coefficients, composite reliability, and Cronbach's alpha all demonstrate strong internal consistency, with each construct in Table 6 explaining 50% or more than 0.7.

Discriminant validity, which measures how much a concept differs experimentally from other elements of the structural model, was evaluated using two techniques. Fornell and Larcker (1981) suggested comparing the AVE of each construct to the square inter-construct correlation of that construct and all other reflectively assessed constructs in the structural model.

The second criterion, known as heterotrait-monotrait (HTMT), was developed by Henseler et al. (2015) to evaluate discriminant validity. According to Henseler et al. (2015), the HTMT is computed by dividing the average correlation value for various constructs by the geometric mean of average correlations for items measuring the same construct. A cutoff value of 0.85 is suggested by Henseler et al. (2015) for structural models with essentially distinct constructs. Tables 7 and 8 demonstrate that the current study has achieved enough discriminant validity based on the evaluation results for the Fornell-Larcker (1981) and HTMT criteria.

Table 7. Using the Fornell-Lacker (1981) standard to assess discriminant validity

Dimensions	AS	AI	CF	TS
Anthropomorphic interaction (AI)	(0.814)			
Assistance (AS)	0.483	(0.833)		
Comfort with AI (CF)	0.720	0.543	(0.865)	
Technological skills (TS)	0.574	0.451	0.764	(0.863)

Note: The diagonal's bolded values correspond to AVE's square root.

Table 8. Employing the HTMT criterion to determine discriminant validity

	AS	AI	CF	TS
Anthropomorphic interaction (AI)				
Assistance (AS)	0.532			
Comfort with AI (CF)	0.792	0.585		
Technological skills (TS)	0.650	0.490	0.840	

Statistical analyses were conducted using the t-test and one-way ANOVA to determine whether there was a statistically significant difference in the means of the study sample concerning AI self-efficacy (assistance, anthropomorphic interaction, comfort with AI, and technological skills), as perceived by mathematics teachers, based on the variables of gender, years of experience, age, and academic level. An independent samples t-test was conducted to compare the influence of gender on the AI self-efficacy construct of assistance among mathematics teachers. Table 9 reports that there was no statistically significant difference in scores for males ($M = 4.02$, $SD = .601$) and females ($M = 4.09$, $SD = .644$; $t(278) = -.907$, $p = .365$, two-tailed). The magnitude of the differences in the means (mean difference = .068, 95% CI: -.215 to .079) was small (eta squared =.003).

This suggests that both male and female mathematics teachers recognize the influence of the AI self-efficacy construct (assistance) in teaching practices. In addition, there is no significant difference in the perception of male and female teachers in terms of the AI self-efficacy construct (comfort with AI). Table 9 reports that there was no statistically significant difference in scores for males ($M = 3.45$, $SD =.750$) and females ($M = 3.56$, $SD = .862$; $t(278) = -1.213$, $p = .226$, two-tailed). The magnitude of the differences in the means (mean difference = -.118, 95% CI: -.308 to .073) was small (eta squared =.005). This suggests that both male and female mathematics teachers recognize the influence of the AI self-efficacy construct (comfort with AI) in teaching practices.

Table 9 reports that there was no statistically significant difference in scores for males ($M = 3.40$, $SD = .718$) and females ($M = 3.48$, $SD = .915$; $t(272) = -.853$, $p = .395$, two-tailed) in terms of technological scales. The magnitude of the differences in the means (mean difference = -.083, 95% CI: -.276 to .109) was small (eta squared = .003). This suggests that both male and female mathematics teachers recognize the influence of the AI self-efficacy construct (technological skills) in teaching practices.

However, there was a statistically significant difference in terms of anthropomorphic interaction for males ($M = 3.41$, $SD = .827$) and females ($M = 3.61$, $SD = .799$; $t(278) = -2.05$, $p = .041$, two-tailed). The magnitude of the differences in the means (mean difference = -.199, 95% CI: -.391 to .008) was small (eta squared = .015). This suggests that female mathematics teachers recognize the influence of the AI self-efficacy construct (anthropomorphic interaction) in teaching practices more than male mathematics teachers.

Table 9. Mathematics teachers' perceptions of AI self-efficacy based on gender

Construct	Gender	N	Mean	SD	df	t	Sig
Assistance	Male	134	4.02	.601	278	-.907	.365
	Female	146	4.09	.644			
Anthropomorphic	Male	134	3.41	.827	278	-2.050	.041
	Female	146	3.61	.799			
Comfort with AI	Male	134	3.45	.750	278	-1.213	.226
	Female	146	3.56	.862			
Technological skills	Male	134	3.40	.718	272	-.853	.395
	Female	146	3.48	.915			

A one-way between-groups analysis of variance was conducted to explore the impact of mathematics teachers' years of teaching experience on their perspectives on AI self-efficacy. Participants were divided into three groups according to their years of teaching experience (Group 1: 5 years or less; Group 2: 6 to 10 years; Group 3: 11 years and above). Table 10 shows that there was a statistically significant difference at the $p < .05$ level in the AI self-efficacy (assistance) scores for the three teaching experience groups: $F(2, 247) = 8.70$, $p = .001$. Despite reaching statistical significance, the actual difference in mean scores between the groups was small. The effect size, calculated using eta squared, was .045. Post-hoc comparisons using the Tukey HSD test indicated that the mean score for Group 2 (6 to 10 years) ($M = 4.28$, $SD = .494$) was statistically significantly different from Group 3 (11 years and above) ($M = 3.98$, $SD = .559$).

There was a statistically significant difference at the $p <.05$ level in the anthropomorphic interaction scores for the three teaching experience groups: $F(2, 277) = 3.628$, $p = .028$. Despite reaching statistical significance, the actual difference in mean scores between the groups was small. The effect size, calculated using eta squared, was .026. Post-hoc comparisons using the Tukey HSD test indicated that the mean score for Group 2 (6 to 10 years) ($M = 3.75$, $SD = .758$) was statistically significantly different from Group 3 (11 years and above) ($M = 3.40$, $SD = .752$).

There was a statistically significant difference at the $p < .05$ level in the comfort with AI scores for the three teaching experience groups: $F(2, 277) = 7.234$, $p = .001$. Despite reaching statistical significance, the actual difference in mean scores between the groups was small. The effect size, calculated using eta squared, was .050. Post-hoc comparisons using the Tukey HSD test indicated that the mean score for Group 1 (5 years or less) (M = 3.62, SD = .862) was statistically significantly different from Group 3 (11 years and above) (M = 3.33, SD = .739).

There was a statistically significant difference at the p <.05 level in the technological skills scores for the three teaching experience groups: F (2, 277) = 6.581, p = .001. Despite reaching statistical significance, the actual difference in mean scores between the groups was small. The effect size, calculated using eta squared, was .045. Post-hoc comparisons using the Tukey HSD test indicated that the mean score for Group 2 (6 to 10 years) (M = 3.69, SD = .857) was statistically significantly different from Group 3 (11 years and above) (M = 3.27, SD = .727).

Table 10. Results of the ANOVA test according to years of experience.

Experience	N	M	SD	Variance sources	Sum of squares	df	Mean square	F	Sig
AS: Assistance									
5 years or less	91	4.11	.736	Between groups	4.892	2	2.446	8.70	.000
6 to 10 years	52	4.28	.494	Within groups	103.741	138	.375		
11 years and above	137	3.98	.559	Total	108.633	140			
AI: Anthropomorphic interaction									
5 years or less	91	3.55	.915	Between groups	4.758	2	2.379	3.628	.028
6 to 10 years	52	3.75	.758	Within groups	181.596	277	.656		
11 years and above	137	3.40	.752	Total	186.354	279			
CF: Comfort with AI									
5 years or less	91	3.62	.862	Between groups	9.102	2	4.551	7.234	.001

6 to 10 years	52	3.77	.807	Within groups	174.248	277	.629		
11 years and above	137	3.33	.739	Total	183.349				
TS: Technological skills									
5 years or less	91	3.57	.898	Between groups	8.642	2	4.321	6.581	.002
6 to 10 years	52	3.69	.857	Within groups	181.875	277	.657		
11 years and above	137	3.27	.727	Total	190.517				

To identify the influence of AI self-efficacy of mathematics educators according to their academic qualifications, a one-way between-groups analysis of variance was conducted. Participants were divided into three groups according to their academic qualifications (Group 1: Higher diploma; Group 2: Bachelor's degree; Group 3: Master's/PhD). Table 11 shows that there was no statistically significant difference at the $p < .05$ level in the influence of AI self-efficacy scores for the three academic qualification groups: $F(2, 277) = .236$, $p = .790$, in terms of AI self-efficacy (assistance). There was no statistically significant difference at the $p < .05$ level in the influence of AI self-efficacy scores for the three academic qualification groups: $F(2, 277) = .950$, $p = .388$, in terms of AI self-efficacy (anthropomorphic interaction).

Similarly, there was no statistically significant difference at the $p < .05$ level in the influence of AI self-efficacy scores for the three academic qualification groups: $F(2, 277) = .234$, $p = .792$, in terms of AI self-efficacy (comfort with AI). Moreover, there was no statistically significant difference at the $p < .05$ level in the influence of AI self-efficacy scores for the three academic qualification groups: $F(2, 277) = .234$, $p = .098$, in terms of AI self-efficacy (technological skills).

Table 11. Results of the ANOVA test according to academic qualifications.

	N	M	SD	Variance sources	Sum of squares	df	Mean square	F	Sig
AS: Assistance									
Higher diploma	37	4.03	.594	Between groups	.185	2	.093	.236	.790

Bachelor's	230	4.06	.623	Within groups	108.448	277	.392		
Masters/ PhD	13	4.16	.753	Total	108.633	279			
AI: Anthropomorphic interaction									
Higher diploma	37	3.34	.933	Between groups	1.269	2	.635	.950	.388
Bachelor's	230	3.54	.789	Within groups	185.084	277	.668		
Masters/ PhD	13	3.52	.971	Total	186.354	279			
CF: Comfort with AI									
Higher diploma	37	3.42	.951	Between groups	.309	2	.154	.234	.792
Bachelor's	230	3.52	.761	Within groups	183.040	277	.661		
Masters/ PhD	13	3.49	1.224	Total	183.349	279			
TS: Technological skills									
Higher diploma	37	3.18	.903	Between groups	3.166	2	1.583	.234	.098
Bachelor's	230	3.48	.799	Within groups	187.351	277	.676		
Masters/ PhD	13	3.62	.993	Total	190.517	279			

To identify the influence of AI self-efficacy of mathematics educators according to their age, one-way between-groups analysis of variance was conducted. Participants were divided into three groups according to their academic qualifications (Group 1: 20–30 years; Group 2: 31–

40 years; Group 3: 41–50 years; Group 4: 51 years or more). Table 12 shows that there was no statistically significant difference at the p < .05 level in the influence of AI self-efficacy scores for the four age groups: F (3, 276) = 2.949, p = .033, in terms of AI self-efficacy (assistance). There was no statistically significant difference at the p < .05 level in the influence of AI self-efficacy scores for the four age groups: F (3, 276) = .724, p = .538, in terms of AI self-efficacy (anthropomorphic interaction).

However, there was a statistically significant difference at the p < .05 level in the influence of AI self-efficacy scores for the four age groups: F (3, 276) = .234, p = .015, in terms of AI self-efficacy (comfort with AI). Despite reaching statistical significance, the actual difference in mean scores between the groups was small. The effect size, calculated using eta squared, was .035. Post-hoc comparisons using the Tukey HSD test indicated that the mean score for Group 1 (20 to 30 years) (M = 3.72, SD = .794) was statistically significantly different from Group 4 (51 years and above) (M = 3.31, SD = .647). Similarly, there was a statistically significant difference at the p < .05 level in the influence of AI self-efficacy scores for the four age groups: F (3, 276) = .234, p = .015, in terms of AI self-efficacy (technological skills). Despite reaching statistical significance, the actual difference in mean scores between the groups was small. The effect size, calculated using eta squared, was .035. Post-hoc comparisons using the Tukey HSD test indicated that the mean score for Group 1 (20 to 30 years) (M = 3.66, SD = .892) was statistically significantly different from Group 4 (51 years and above) (M = 3.23, SD = .650).

Table 12. Results of the ANOVA test according to age.

	N	M	SD	Variance sources	Sum of squares	df	Mean square	F	Sig
AS: Assistance									
20–30 years	88	4.19	.677	Between groups	3.375	3	1.125	2.949	.083
31-40 years	84	4.09	.593	Within groups	105.258	276	.381		
41-50 years	67	3.94	.608	Total	108.633	279			
50 years or more	41	3.91	.543						
AI: Anthropomorphic interaction									
20–30 years	88	3.62	.888	Between groups	1.455	3	.485	.724	.538

31-40 years	84	3.45	.884	Within groups	184.899	276	.670		
41-50 years	67	3.50	.726	Total	186.354	279			
50 years or more	41	3.45	.648						
CF: Comfort with AI									
20–30 years	88	3.72	.794	Between groups	6.336	3	2.112	3.62	.015
31-40 years	84	3.41	.923	Within groups	177.03	276	.641		
41-50 years	67	3.47	.726	Total	183.349	279			
50 years or more	41	3.31	.647						
TS: Technological skills									
20–30 years	88	3.66	.892	Between groups	6.589	3	2.196	3.296	.021
31-40 years	84	3.38	.846	Within groups	183.928	276	.666		
41-50 years	67	3.37	.763	Total	190.517	279			
50 years or more	41	3.23	.650						

The Teachers' Artificial Intelligence Self-Efficacy (TAISE) scale was validated in this study, offering a reliable tool to assess teachers' self-efficacy with AI in four areas: assistance, anthropomorphic interaction, comfort with AI and technological skills. Among Bahraini math teachers, the TAISE scale showed good psychometric qualities, and confirmatory factor analysis confirmed its structural soundness. These results are consistent with earlier studies that highlight the significance of trustworthy self-efficacy metrics for integrating technology into the classroom (Tondeur et al., 2017; Paetsch et al., 2023).

The study found that most math teachers had good AI self-efficacy, with mean scores above the midpoint of the scale. This supports earlier research demonstrating that a stronger readiness to accept and use instructional technologies is correlated with better levels of self-efficacy (Bandura, 1997). Interestingly, the AI self-efficacy components were not significantly impacted by gender, except for anthropomorphic interaction, where female teachers reported stronger impressions. Men may place more emphasis on perceived utility, while women may report feeling more at ease in specific technology-related interactions. These findings are consistent with recent research that suggests gender differences in technology adoption are complex (Masry-Herzallah, 2025; Zhao et al., 2024;).

One important element was teaching experience; instructors with 6–10 years of experience reported higher levels of AI self-efficacy across a number of categories than teachers with more than 11 years. This trend points to a possible mid-career high in AI self-efficacy, which could be brought on by a mix of experience gained and further professional growth. Studies looking at the connection between technology integration self-efficacy and teaching experience have found similar patterns (Ertmer & Ottenbreit-Leftwich, 2010; Justol & Potane, 2024).

Age-related differences were also noted, with younger educators (those between the ages of 20 and 30) expressing greater ease with artificial intelligence and technology than their more senior peers. This result is consistent with studies showing that younger educators, who are frequently digital natives, are more comfortable and confident using new technology (Hatlevik & Hatlevik, 2018). Academic qualifications, however, had no apparent influence on AI self-efficacy, indicating that exposure to and experience in the real world may have a greater impact on instructors' confidence in AI than formal schooling.

5. Limitation and Further Studies

While this study provides meaningful insights into the self-efficacy of mathematics teachers regarding artificial intelligence, certain limitations must be recognized. The investigation was limited to a sample of 280 teachers from government schools in Bahrain, and data collection depended primarily on responses to an open-ended question. Expanding the participant pool to include teachers from private institutions and different educational contexts could yield a more nuanced and comprehensive understanding of Math Teachers' Artificial Intelligence Self-Efficacy. Future studies would benefit from incorporating a more diverse representation of educators to enhance the generalizability of findings. Additionally, the study's results are inherently linked to the validity and reliability of the instruments employed. Given the rapid evolution of AI technologies and their applications in education, teachers' perceptions, practices, and self-efficacy are likely to shift over time, either positively or negatively, as they encounter emerging tools and methodologies.

To support the integration of AI in educational settings, several recommendations can be proposed. Targeted professional development programs should be designed and implemented to strengthen teachers' proficiency in using AI, thereby enhancing their confidence and self-efficacy in adopting such technologies. Curriculum development efforts should not be confined to mathematics but should instead embrace AI-related concepts across disciplines, fostering an interdisciplinary framework that aligns with 21st-century learning demands.

Future research should prioritize longitudinal studies to examine the enduring impact of AI adoption on teachers' self-efficacy and instructional practices. Moreover, investigations into the ethical dimensions of AI, strategies for safeguarding data privacy, and institutional preparedness for large-scale AI integration will be critical in shaping the future landscape of education.

6. Conclusion

The study's conclusions present a convincing picture of Bahraini math teachers' self-efficacy with AI tools. A comprehensive grasp of how educators view and use AI in the classroom is made possible by the validated TAISE scale's strong psychometric qualities across four important domains (Assistance, Anthropomorphic interaction, Comfort with AI, and Technological skills). There were gender disparities in anthropomorphic interaction, with female teachers feeling more at ease, despite the high level of overall self-efficacy. In contrast to teachers with more than 11 years of experience, mid-career teachers (6–10 years) had noticeably higher AI self-efficacy across all categories, indicating a vital window for support and skill development. Younger teachers also demonstrated greater comfort and technological adaptation while utilizing AI. However, there was no significant effect from academic credentials, underscoring the importance of practical experience and digital fluency. These conclusions encourage policymakers and educational leaders to support ongoing AI integration initiatives and personalized training based on age and experience profiles. By providing teachers with ongoing professional development, we can make sure AI promotes rather than impedes educational innovation.

References

Achurra, C., & Villardón, L. (2012). Teacher' self-efficacy and student learning. *The European Journal of Social & Behavioural Sciences, 2*(2), 367-383. http://dx.doi.org/10.15405/FutureAcademy/ejsbs(2301-2218).2012.2.17

Alabed, A., Javornik, A., & Gregory-Smith, D. (2022). AI anthropomorphism and its effect on users' self-congruence and self–AI integration: A theoretical framework and research agenda. *Technological Forecasting and Social Change, 182*(121786), 1-19. https://doi.org/10.1016/j.techfore.2022.121786.

Al-Hadrawi, B. K., Al-Hadrawi, K. K., Ezzerouali, S., Al-Hadraawy, S. K., Aldhalmi, H. K., & Alshawabkeh, M. A. (2025). Narratives of Comfort and Convenience: Exploring Artificial Intelligence's Role in Alleviating Consumer Anxiety: Legal Aspects. *Journal of Lifestyle & SDG'S Review, 5* (3), 1-30. https://doi.org/10.47172/2965-730X.SDGsReview.v5.n03.pe03865

AlKanaan, H. M. N. (2022). Awareness regarding the implication of artificial intelligence in science education among pre-service science teachers. *International Journal of Instruction, 15*(3), 895-912. https://doi.org/10.29333/iji.2022.15348a

Antonenko, P., & Abramowitz, B. (2023). In-service teachers' (mis)conceptions of artificial intelligence in K-12 science education. *Journal of Research on Technology in Education, 55*(1), 64-78. https://doi.org/10.1080/15391523.2022.2119450

Arnado, A. A., Pene, A. J. P., Fuentes, C. J. F., & Astilla, K. M. (2022). Fostering sustainable STEM education: Attitudes and self-efficacy beliefs of STEM teachers in conducting laboratory activities. *International Journal of Studies in Education and Science (IJSES), 3*(1), 54-74.

Bagozzi, R. P., Yi, Y., & Phillipps, L. W. (1991). Assessing construct validity in organizational research. *Administrative Science Quarterly, 36*, 421-458. https://doi.org/10.2307/2393203

Bandura, A. B. (1997). Self-efficacy: The exercise of control. New York, NY: Freeman.

Bate, G. W., & Eberhard, A. (2024). Enhancing reflective practices in higher education with AI-supported anthropomorphic coaches. *ASCILITE Publications,* 1-6. https://doi.org/10.14742/apubs.2024.1424

Berger, J. L., Girardet, C., Vaudroz, C., & Crahay, M. (2018). Teaching Experience, Teachers' Beliefs, and Self-Reported Classroom Management Practices: A Coherent Network. *SAGE Open*, *8*(1), 1-12. https://doi.org/10.1177/2158244017754119

Bhati, K., & Sethy, T. P. (2022). Self-efficacy: Theory to educational practice. *The International Journal of Indian Psychology*, *10*(1), 1123-1128. https://doi.org/10.25215/1001.112

Bilad, M. R., Yaqin, L. N., & Zubaidah, S. (2023). Recent Progress in the Use of Artificial Intelligence Tools in Education. *Jurnal Penelitian dan Pengkajian Ilmu Pendidikan: e-Saintika, 7*(3), 279-314. https://doi.org/10.36312/esaintika.v7i3.1377

Bray-Clark, N., & Bates, R. (2003). Self-efficacy beliefs and teacher effectiveness: Implications for professional development. *Professional educator, 26*(1), 13-22.

Byrne, B. (2016). *Structural Equation Modeling with AMOS: Basic Concepts, Applications and Programming*; Routledge: Abingdon, UK.

Channawar, S. (2023). Teacher Self-Efficacy: Influences Pedagogical Skill Among Students Learning. *UGC Care Group I Journal, 83*(23), 183-187.

Chiu, T. K. F., Ahmad, Z., & Çoban, M. (2024). Development and validation of teacher artificial intelligence (AI) competence self-efficacy (TAICS) scale. *Education and Information Technologies*, 1-19. https://doi.org/10.1007/s10639-024-13094-z

Chou, C. M., Shen, T. C., Shen, T. C., & Shen, C. H. (2023). The level of perceived efficacy from teachers to access AI-based teaching applications. *Research and Practice in Technology Enhanced Learning, 18*(21), 1-26. https://doi.org/10.58459/rptel.2023.18021

Demir, A. N. (2021). An extended literature review on in-service EFL teachers' self-efficacy beliefs. *Focus on ELT Journal*, *3*(2), 36-50. https://doi.org/10.14744/felt.2021.3.2.3

Dijkstra, T. K., & Henseler, J. (2015). Consistent partial least squares path modeling. *MIS Quarterly, 39*(2), 297-316. https://doi.org/10.25300/MISQ/2015/39.2.02

Dzin, N. H. M., & Lay, Y. F. (2021). Validity and reliability of adapted self-efficacy Scales in Malaysian context using PLS-SEM approach. *Education Sciences, 11* (676), 1-22. https://doi.org/10.3390/educsci11110676.

Er, K. O. (2020). The Relationship between Teacher Self-Efficacy Beliefs and Educational Beliefs of Pre-Service Teachers. *Educational Research and Reviews*, *15*(1), 8-18. https://doi.org/10.5897/ERR2019.3820

Ertmer, P. A., & Ottenbreit-Leftwich, A. (2010). Teacher Technology Change: How Knowledge, Beliefs, and Culture Intersect. *Journal of Research on Technology in Education, 42*(3),255-284. https://doi.org/10.1080/15391523.2010.10782551

Fitria, T. N. (2023). The Use of Artificial Intelligence in Education (Aied): Can AI Replace the Teacher's Role?. *Epigram, 20*(2), 165-187. https://doi.org/10.32722/epi.v20i2.5711

Fornell, C. G., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50. https://doi.org/10.2307/3151312

Gale, J., Alemdar, M., Cappelli, C., & Morris, D. (2021). A mixed methods study of self-efficacy, the sources of self-efficacy, and teaching experience. *Frontiers in Education, 6*(750599), 1-16. https://doi.org/10.3389/feduc.2021.750599

Galindo-Domínguez, H., Delgado, N., Losada, D., & Etxabe, J.M. (2024). An analysis of the use of artificial intelligence in education in Spain: the in-service teacher's perspective. *Journal of Digital Learning in Teacher Education, 40*(1), 41-56. http://dx.doi.org/10.1080/21532974.2023.2284726

Gocen, A., & Aydemir, F. (2020). Artificial Intelligence in Education and Schools. *Research on Education and Media, 12*(1), 13-21. https://doi.org/10.2478/rem-2020-0003.

Gomes, S., Lopes, J. M., & Nogueira, E. (2025). Anthropomorphism in artificial intelligence: a game-changer for brand marketing. *Future Business Journal (11)*2, 1-15. https://doi.org/10.1186/s43093-025-00423-y

Gordon, D., Blundell, C., Mills, R., & Bourke, T. (2023). Teacher self-efficacy and reform: a systematic literature review. *The Australian Educational Researcher*, *50*(3), 801-821. https://doi.org/10.1007/s13384-022-00526-3

Hair, J. F., Anderson, R. E., Babin, B. J., Black, W. C. (2010). Multivariate Data Analysis: A Global Perspective; Pearson Education: London, UK.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed, A Silver Bullet. *J. Mark. Theory Pract., 19*(2), 139-152. https://doi.org/10.2753/MTP1069-6679190202

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. A. (2014). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), 1st ed., SAGE Publications: Thousand Oaks, CA, USA.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, Sage, Thousand Oaks, CA.

Hair, J. F., Risher, J., J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hair, J. F., Hult G. T. M., Ringle CM, et al. (2022) *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 3rd ed., Sage, Thousand Oaks, CA.

Hatlevik, O. E., & Hatlevik, S. (2018). Examining the relationship between teachers' self-efficacy, their digital competence, strategies to evaluate information, and use of ICT at school. *Scandinavian Journal of Educational Research, 62*(5), 555-567. https://doi.org/10..3389/fpsyg.2018.00935

Harrington, D. (2009). Confirmatory factor Analysis. New York, NY: Oxford University Press.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modelling. *Journal of the Academy of Marketing Science, 43*(1), 115-135. https://doi.org/10.1007/s11747-014-0403-8

Henson, R. K. (2001, January 26). *Teacher self-efficacy: Substantive implications and measurement dilemmas* [presentation paper]. The Educational Research Exchange Annual Meeting, College Station, TX, United States.

Hulland, J. (1999). Use of Partial Least Squares (PLS). In Strategic Management Research: A Review of Four Recent Studies. *Strategic Management Journal, 20*(2), 195-204. https://doi.org/10.1002/(SICI)1097-0266(199902)20:2<195::AID-SMJ13>3.0.CO;2-7

Hussain, M. S., & Khan, S. A. (2022). Self-efficacy of teachers: A review of the literature. *Multi-Disciplinary Research Journal*, *10*(1), 110-116.

Jerrim, J., Sims, S., & Oliver, M. (2023). Teacher self-efficacy and pupil achievement: much ado about nothing? International evidence from TIMSS. *Teachers and Teaching*, *29*(2), 220-240. https://doi.org/10.1080/13540602.2022.2159365

Joreskog, K.G. (1971). Statistical analysis of sets of congeneric tests. *Psychometrika, 36*, 109–133. https://doi.org/10.1007/BF02291393

Justol, D. D. P. & Potana, J. D. (2024). Demographics and Technology Integration in Teaching English on the Relationship Between Teachers' Technology Self-Efficacy and Performance. *American Journal of Educational Research,12*(3), 99-108. https://doi.org/10.12691/education-12-3-4

Kaiser, H. (1974). An index of factorial simplicity. *Psychometrika, 39,* 31-36. https://doi.org/10.1007/BF02291575

Kline, R. B. (2016). Principles and practices of structural equation modeling (4th ed.). Guilford Press.

Lazarides, R., & Warner, L. (2020, May 29). Teacher Self-Efficacy. *Oxford Research Encyclopedia of Education.* Retrieved 6 Jul. 2025, from https://doi.org/10.1093/acrefore/9780190264093.013.890

Nunnally, B. & Bernstein, I. R. (1994). Psychometric Theory; Oxford University: Oxford, UK.

Masry-Herzallah, A., & Watted, A. (2024). Technological Self-efficacy, Mindfulness Ability, and the Effectiveness of Online Learning among Arab Students in Higher Education Settings during the COVID-19 Crisis. *Contemporary Educational Technology, 16*(2), 1-13. https://doi.org/10.30935/cedtech/14336

Opingo, K. M. M., & Linox, D. (2024). Teachers' Self-Efficacy, Attitudes, and Challenges in the Implementation of Inclusive Education. *World Journal on Education and Humanities Research, 4*(1), 136-145.

Oran, B. B. (2023). Correlation between artificial intelligence in education and teacher self-efficacy beliefs: a review. *RumeliDE Dil ve Edebiyat Araştırmaları Dergisi, 34*, 1354-1365. https://doi.org/10.29000/rumelide.1316378

Paetsch, J., Franz, S., & Wolter, I. (2023). Changes in early career teachers' technology use for teaching: The roles of teacher self-efficacy, ICT literacy, and experience during COVID-19 school closure. *Teaching and Teacher Education, 135*(104318), 1-11. https://doi.org/10.1016/j.tate.2023.104318

Parsakia, K. (2023). The Effect of Chatbots and AI on The Self-Efficacy, Self-Esteem, Problem-Solving and Critical Thinking of Students. *Health Nexus*, *1*(1), 71-76. https://doi.org/10.61838/hn.1.1.14

Placani, A. (2024). Anthropomorphism in AI: hype and fallacy. *AI Ethics, 4*, 691–698. https://doi.org/10.1007/s43681-024-00419-4

Rahman, A. A., Yaakub, M., Halili, S. H., & Razak, R. A. (2022). SIGNIFICANT EFFECT OF THE TPACK FRAMEWORK ON TEACHERS'SELF-EFFICACY: A SYSTEMATIC LITERATURE REVIEW. *Journal of Educational Research, 40*, 63-79.

Sapna, S. (2017). *Professional Commitment, rule conflict and self efficacy as related to change proneness among secondary school teacher* [Doctoral dissertation, Himachal Pradesh University]. Himachal Pradesh University Theses and Dissertations Archive.

Shah, D. (2023). Teachers' Self-Efficacy and Classroom Management Practices: A Theoretical Study. *Journal of Education and Research*, *13*(1), 8-26. https://doi.org/10.51474/jer.v13i1.661

Tondeur, J., Braak, J. V., Ertmer, P. A., & Ottenbreit-Leftwich, A. (2017). Understanding the relationship between teachers' pedagogical beliefs and technology use in education: A systematic review of qualitative evidence. *Educational Technology Research and Development, 65*(3), 555-575. https://doi.org/10.1007/s11423-016-9481-2

Wang, Y. Y., & Chuang, Y. W. (2024). Artificial intelligence self-efficacy: Scale development and validation. *Education and Information Technologies*, *29*(4), 4785-4808. https://doi.org/10.1007/s10639-023-12015-w

Woodcock, S., & Hardy, I. (2023). Teacher self-efficacy, inclusion and professional development practices: cultivating a learning environment for all. *Professional Development in Education*, 1-15. https://doi.org/10.1080/19415257.2023.2267058

Yufeia, L., Salehb, S., Jiahuic, H., & Syed, S. M. (2020). Review of the application of artificial intelligence in education. *Integration (Amsterdam)*, *12*(8), 548-562. https://doi.org/10.53333/IJICC2013/12850

Zhao, Y., Sun, T., Zhang, X., Wang, X., & Hu, W. (2024). The evolution of medical education in the era of COVID-19 and beyond: A longitudinal study. *BMC Medical Education, 24*(1289), 1-11. https://doi.org/10.1186/s12909-024-06271-8

Copyrights