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Research Article

Factors Affecting Teachers' Acceptance of Artificial Intelligence Technologies: Analyzing Teacher Perspectives with Structural Equation Modeling

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Abstract

Recent advances in artificial intelligence (AI) technologies have brought to the agenda how to encourage the use of these technologies in education. Teachers' acceptance of AI technologies has an important place. This study, based on the Technology Acceptance Model (TAM), investigates the factors affecting teachers' acceptance of AI technologies. A five-structure structural model for AI technology was proposed by adding Self-Efficacy and Anxiety to TAM. A trial form consisting of 21 items was prepared and 18 items were confirmed. Structural Equation Modeling (SEM) was used to analyze the data. In the proposed model, 7 hypotheses related to Self-Efficacy (SE), Artificial Intelligence Anxiety (AIA), Perceived Ease of Use (PEU), Perceived Utility (PU) and Behavioral Intention (BI) were tested. A significant negative effect was obtained with H1, H2 and H7; a significant positive effect was obtained with H3, H4 and H6, while H5 was not confirmed. The effect of teachers' perceived ease of use on perceived usefulness (H3) and the effect of perceived usefulness on behavioral intention (H6) were the strongest positive effects in the model. The effect of AI anxiety on perceived ease of use (H2) was the strongest negative effect. It was found that teachers' acceptance of using AI technologies in teaching is predictable by teachers' self-efficacy towards AI, AI anxiety and perceived usefulness. The results of this study contributed to the extension of TAM. This study presents a TAM study on AI technologies. In addition, the results can help future educational planning in the use of educational technologies.

Keywords: Artificial intelligence anxiety, Self-efficacy, Technology acceptance model, Structural equation model, Teachers

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Öğretmenlerin Yapay Zekâ Teknolojilerini Kabulünü Etkileyen Faktörler: Yapısal Eşitlik Modeli ile Öğretmen Bakış Açılarının Analizi

Özet

Yapay zekâ teknolojilerindeki hızlı ilerlemeler, eğitimde bu teknolojilerin kullanımının nasıl teşvik edileceğini gündeme getirmiştir. Öğretmenlerin yapay zekâ teknolojilerini kabulü bu bakımdan önemli bir yere sahiptir. Teknoloji Kabul Modeli'ne (TKM) dayanan bu çalışma, öğretmenlerin yapay zekâ teknolojilerini kabulünü etkileyen faktörleri araştırmaktadır. Bu amaçla TKM'ye Öz-yeterlik ve Kaygı eklenerek yapay zekâ teknolojisine yönelik beş yapılı bir yapısal model önerilmiştir. Verilerin toplanması için 21 maddeden oluşan bir ölçek hazırlanmıştır. 18 madde Doğrulayıcı Faktör Analizi ile doğrulanmıştır. Verilerin analizinde Yapısal Eşitlik Modeli kullanılmıştır. Önerilen modelde, Öz-yeterlik (ÖY), Yapay Zekâ Kaygısı (YZK), Algılanan Kullanım Kolaylığı (AKK), Algılanan Fayda (AF) ve Davranışsal Niyet (DN) ile ilgili 7 hipotez test edilmiştir. Hipotezlerden H1, H2 ve H7 ile anlamlı bir negatif etki; H3, H4 ve H6 ile ise anlamlı bir pozitif etki elde edilirken H5 doğrulanmamıştır. Öğretmenlerin Algılanan kullanım kolaylığının Algılanan faydası üzerindeki etkisinin (H3) ve Algılanan Faydasının Davranışsal niyeti üzerindeki etkisinin (H6) sırasıyla modeldeki en güçlü olumlu etkiler olduğu tespit edilmiştir. Yapay zekâ kaygısının Algılanan kullanım kolaylığının üzerindeki etkisinin (H2) ise en güçlü negatif etki oldğu tespit edilmiştir. Çalışmada öğretmenlerin öğretimde yapay zekâ teknolojilerini kullanmayı kabullerinin, öğretmenlerin yapay zekâya yönelik öz-yeterliği, yapay zekâ kaygısı ve algılanan faydası tarafından tahmin edilebilir olduğu tespit edilmiştir. Bu çalışmanın sonuçları TKM'nin genişletilmesine katkıda bulunmuştur. Bu çalışma Türkiye'de alanyazındaki önemli bir boşluğu doldurarak yapay zekâ teknolojilerini konu alan bir TKM çalışması sunmaktadır. Ayrıca çalışmanın sonuçları, eğitim teknolojilerinin kullanılmasında gelecekteki eğitim planlamalarına yardımcı olabilecek niteliktedir.

Anahtar Kelimeler: Yapay zekâ kaygısı, Öz-yeterlik, Teknoloji kabul modeli, Yapısal eşitlik modeli, Öğretmenler

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1. Introduction

Technology, one of the products of change and development today, renews itself day by day. This adventure, which started with simple technologies, progresses towards very complex structures. The emergence of computers, one of the technological devices, has shown that machines with intelligence-related capabilities can be made (Çetin & Aktaş, 2021). The type of intelligence offered through these machines is characterized as artificial intelligence (Güzey et al., 2022). The concept of artificial intelligence was first introduced by McCarthy in 1956 as "the science and engineering of making intelligent machines" (Hamet & Tremblay, 2017). Artificial intelligence technology is utilized in many areas of daily life. For example, optimizing drivers' route on Google Maps, ordering emails into a user's spam mail folder, recommending products that might be liked in an e-commerce environment, and supporting automated driving (Antonenko & Abramowitz, 2023).

Artificial intelligence, one of the innovations of technology, has started to gain a place in education while progressing rapidly in social life. In this context, creating smart learning environments, innovating smart education models, improving teacher training and developing management skills have been emphasized (Ma & Lei, 2024). Artificial intelligence is an undeniable technology that contributes to education for reasons such as helping lesson to be expertly, interesting and fun, finding the appropriate teaching materials for students, and ensuring the persistence of learning by making learning processes easier (Nabiyev & Erümit, 2020). Artificial intelligence enables personalization of courses in education, organization of curriculum, identification of knowledge gaps, provision of rapid feedback to students, increase of efficiency of instructors and training of future innovators (Nuangchalerm & Prachagool 2023).

Technology Acceptance Model

TAM was created to determine the adopting and using new communication technologies by individuals (Venkatesh & Bala, 2008). The TAM states that individuals' behavioral intention to use a communication technology is determined by two beliefs and assumes that this behavioral intention predicts actual use (Heerink et al., 2014). These are perceived usefulness and perceived ease of use (Venkatesh & Bala, 2008). Also in TAM, behavioral intention is a determinant of technology adoption and use (Al-Adwan, et al., 2023).

TAM helps researchers to find out factors that have the potential to drive the adoption or acceptance of a particular technology (Lee et al., 2019). In recent years, TAM-based studies have been conducted to identify the factors that shape teachers' and pre-service teachers' perspectives on the use of technology in education. These studies were carried out by integrating different instructional technologies into TAM. Web-based e-learning systems, mobile learning technologies, Metaverse-based learning platforms and artificial intelligence technologies are some of them (Al-Adwan, et al., 2023; Chen & Tseng, 2012; Chen, et al., 2023; Mac Callum et al., 2014; Wang, et al., 2022). In this study, TAM was used to determine the factors affecting teachers' acceptance of AI technologies.

Self-efficacy

According to Bandura (1997), self-efficacy is the belief in one's capacity to organize and perform the activities required to achieve certain outcomes. Self-efficacy focuses on performance abilities rather than personal qualities such as physical or psychological characteristics of the individual and judges the individual's ability to fulfill the given task, not who he/she is or how he/she feels about himself/herself" (Zimmerman, 2000). Self-efficacy guides behavior by influencing people's activity choices, efforts and determination in the face of challenges. High self-efficacy increases continuous participation in activities and success (Schunk, 1981). Self-efficacy, which can be adapted to different fields (Bandura, 1997), has been discussed in many contexts such as technology self-efficacy (Durak, 2018), computer self-efficacy (Işıksal & Aşkar, 2003), internet self-efficacy (Kim & Glassman, 2013).

In this study, Artificial Intelligence Self-Efficacy was used to determine teachers' perceptions of their ability to use artificial intelligence technologies. There are studies showing that self-efficacy is an important factor in technology adoption (Abdullah et al., 2016; Chahal & Rani, 2022). Individuals who are more confident in their learning skills related to the use of technology tend to see using technology as easy and useful compared to those who are less confident (Venkatesh & Davis, 1996). Aktürk and Delen (2020) indicated that as technology acceptance level increases in teachers, self-efficacy also increases. In this study, self-efficacy was used to determine teachers' self-efficacy perceptions about the use of artificial intelligence technologies.

Artificial Intelligence Anxiety

Anxiety is the uneasiness or irrational fear that arises because people are afraid of any dangerous situation (Manav, 2011). The fact that artificial intelligence (AI) technologies cause anxious or emotional reactions while being used is referred to as AI anxiety (Heerink, et al., 2014). Artificial intelligence anxiety is classified as "job replacement anxiety, sociotechnical blindness, AI configuration anxiety and AI learning anxiety (Wang & Wang, 2022). Research has revealed that teachers' and university instructors' attitudes towards adopting technologies while teaching are affected by their anxiety (Şahin, & Şahin, 2021; Ursavaş, 2014; Wang et al., 2021). In this study, AI anxiety was used to determine teachers' anxiety about the use of Al technologies.

It is not certain that teachers will adopt new technologies if they are not predisposed to them (Chen et al., 2020). Knowing teachers' positions towards the acceptance of artificial intelligence technologies is significant for the development of technology-supported teaching. The fact that the Artificial Intelligence Applications Course Curriculum will be applied to 7th and 8th grade students in Turkey in the 2024-2025 makes teachers' acceptance of artificial intelligence technologies important. This study presents a model based on TAM to examine the factors affecting teachers' acceptance of AI technologies. Teachers' active use of educational technologies is thought to be related to technology acceptance (Aktürk & Delen, 2020). In this study, TAM was used to investigate the acceptance of AI technologies due to its solid theoretical foundation. The TAM has been integrated into different types of technologies and extended with other factors that are assumed to affect intention to use or usage (Heerink et al., 2014).

In their study, Çelik et al. (2024) aimed to determine the effects of perceived usefulness, perceived ease of use, hedonic motivation, value and attitude on behavioral intentions related to distance education applications. In the study, it was determined that usefulness, ease of use and value had a positive and significant effect on attitude, while hedonic motivation did not have a significant effect on attitude. In addition, it was determined that attitude had a positive and significant effect on behavioral intention. Ursavaş et al. (2019) aimed to investigate the effect of subjective norms on teachers' perceptions, attitudes and behavioral intentions towards using computer technology. The results revealed that attitude towards using computer was the most dominant predictor of behavioral intention in teachers. Gurer (2021) investigated the intentions of prospective teachers to use technology in their future teaching by expanding TAM with different variables such as facilitating conditions, subjective norms and technology self-efficacy. The results showed that facilitating conditions, subjective norms and attitudes were important predictors of intention to use technology. In addition, technology self-efficacy significantly determined perceived ease of use. When looking at the studies conducted in Turkey, no TAM study was found in which self-efficacy and anxiety towards AI were integrated. In the current study, teachers' acceptance levels of AI technology were investigated by adding the factors of self-efficacy and anxiety towards AI technologies. Thus, it can be said that this gap in the literature will be filled by adding a TAM study on AI technologies to the literature.

In addition, when the limited number of studies on AI in Turkey is examined, it is seen that there are also few studies in which teachers or teacher candidates constitute the participant group. Ağmaz and Ergüleç (2024) aimed to reveal the views of teacher candidates on the use of AI in education through metaphors. According to the results, the metaphors of teacher candidates who have previously used AI tools are more positive and free from anxiety. The metaphors of those who have not used AI tools are more negative and anxious. Demir Dülger and Gümüşeli (2023) examined the views of school principals and teachers on the use of AI in education in their study. According to the results, the use of AI in education is considered an opportunity and it is seen that it will provide benefits in various areas. Seyrek et al. (2024) aimed to obtain the views of teachers on AI in their study. It was revealed that teachers perceive the role that AI will undertake in the field of education in the future as impressive, positive and exciting. Teachers stated that they prefer AI mostly in the areas of question preparation, content creation, activity preparation, data analysis and success tracking. In addition, it has been observed that the use of AI in education raises concerns such as reduces creativity, students becoming lazy, and data breaches. Balıkçı et al. (2024) aimed to examine teachers' perspectives on the concept of AI using the metaphor analysis method. The results showed that teachers conceptualized AI as a job facilitator by associating it with robots and machines representing cognitive intelligence. In addition, concerns were also identified about the potential risks of AI and its impact on creativity. No study has been found in the Turkish literature examining self-efficacy and artificial intelligence anxiety towards artificial intelligence together. For this reason, the current study is important both in terms of being a study that includes these together and examining these components together with TAM. In this direction, a 5-structure model related to the acceptance of AI technologies was created by integrating AI into TAM. Relational hypotheses based on this model are presented below:

- H1: Self-efficacy towards AI has a significant negative effect on AI anxiety
- H2: AI anxiety has a significant positive effect on the PEU of AI technology.
- H3: PEU of AI technology has a significant positive effect on its PU.
- H4: Self-efficacy towards AI has a significant positive effect on intentions to use it.
- H5: PEU of AI technology has a significant positive effect on behavioral intentions to use it.
- H6: PU of AI technology has a significant positive effect on behavioral intentions to use it.
- H7: AI anxiety has a significant negative effect on behavioral intentions to use it.

2. Method

The descriptive scanning method, one of the quantitative research methods, was used in this research. Descriptive scanning method is a research method that aims to describe an event that has happened in the past or is actively ongoing (Karasar, 2016).

Working Group

Primary and middle school teachers working in two different provinces of Turkey in 2023-2024 academic year were selected as study group. The participants of the study were selected using purposive sampling method. This method requires a selection based on participants' compliance with the screening conditions and their knowledge or expertise on the topic (Palinkas et al., 2015). In the study, data were obtained from separate groups for Exploratory Factor Analysis (EFA) and SEM. Data were obtained from 132 participants (Group 1) for EFA and 174 participants (Group 2) for SEM. It is stated that the number of participants for EFA should be at least 5 per item (Hair et al., 2005). Therefore, the number of items in the study being 21 requires at least 105 participants. For the study, a participant group of 132 participants was reached and a sufficient number was obtained for EFA. 89 participants in Group 1 were female and 43 were male. Of this group, 66 were primary school teachers and 66 were middle school teachers. In SEM analysis, the reasonable sample size for normally distributed data is approximately N = 150 (Muthén & Muthén, 2002). Kline (2023) stated that the acceptable sample size for educational measurements using Structural Equation Modeling (SEM) varies between 100 and 150. Therefore, a participant group of 174 participants was reached for the study and a sufficient number was obtained for SEM analysis. Of this group, 98 were female, 76 were male, 86 were primary school teachers and 88 were middle school teachers.

Data Collection

A scale consisting of 21 items and two parts was prepared for the purpose of the study. The first part of this scale, includes gender and school level information. In the second part, the scale items based on the theoretical model (TAM) were included. The five constructs in TAM are Self-Efficacy (SE), Artificial Intelligence Anxiety (AIA), Perceived Ease of Use (PEU), Perceived Utility (PU) and Behavioral Intention (BI). Each construct in the scale is represented by more than one item. SE contains 5 items (e.g., I can use AI technologies without any problems even though I have not used them before), AIA contains 4 items (Learning to use a new AI technology makes me anxious), PEU contains 4 items (The functioning of an AI-based system is clear and understandable), PU contains 4 items (I think that using AI technologies is beneficial for me), and BI contains 4 items (I plan to spend time exploring new features of AI applications in the future). Ethics committee permission was obtained before collecting data. This study was conducted by the Inonu University Scientific Research and Ethics Committee with the ethics committee decision dated 22/02/2024 and numbered E.414965. The data of the study were collected in the spring semester of the 2023-2024 academic year. Data collection was carried out through Google Forms.

Scale Development Process

In the scale development process, the items were adapted from reliable tools and 23 items related to artificial intelligence technologies were created (Ng, et al., 2023; Venkatesh & Bala, 2008; Wang, et al., 2019; Wang, et al., 2021; Zhang et al., 2023). These items were presented to experts from the fields of Computer and Communication Technologies, Measurement and Evaluation, and Guidance and Psychological Counseling. After the expert evaluation, some of the statements were modified, two repeated items were removed and the items were reshaped by making corrections. Thus, a 21-item trial form was obtained. This scale was read by twelve teachers and corrections were made in the parts that were not comprehensible. This scale was formed in 5-point Likert type and was graded as Completely agree (5), Agree (4), Partially agree (3), Disagree (2), Strongly disagree (1).

First, EFA was conducted using the data of the first study group. SPSS 25.0 program was used to calculate descriptive statistics. Before starting the factor analysis, skewness and kurtosis values of the items were examined. These values ranged between -.774 and .737; -.833 and .451, respectively. It can be said that these values are within acceptable limits for the normality assumption (Büyüköztürk, 2014).

Kaiser-Meyer-Olkin (KMO) and Barlett's test of sphericity were calculated to test the adequacy of the data set for factor analysis. Barlett test (x2 =1754.983; sd= 210; p=0.000) and KMO test (0.886) showed that the data set was suitable for the analysis (Kaiser, 1974). Principal component analysis and Varimax rotation technique were used for EFA. As a result of EFA, 3 items (AIA4, PEU2, and SE5) that did not meet the criteria for factor formation process (Büyüköztürk, 2014; Çokluk, et al., 2021) were removed from the trial form. After the first rotation, since AIA4 was included as a single item under a separate factor, it was removed from the scale. The analysis was repeated and it was determined that the difference between the loading values of PEU2 and SE5 and the loading values in another factor was not higher than .10. Thus, three items were removed from the trial form and a 5-factor structure with 18 items was obtained. This 5-factor structure explains 76.23% of the total variance. After rotation, the first factor contributed 18.98%, the second 16.50%, the third 14.86%, the fourth 14.76% and the fifth 11.13% of the total variance. The factor loadings of the scale items and their contributions to the common variance are given in Table 1.

Table 1.

Factor Loadings

Item	F. Loadings Before Rotation	F1	F2	F3	F4	F5
PU1	.763	.811				
PU3	.754	.810				
PU2	.841	.798				
PU4	.774	.721				
SE4	.826		.882			
SE1	.761		.837			
SE2	.742		.777			
SE3	.657		.541			
BI4	.798			.745		
BI3	.767			.744		
BI2	.782			.658		
BI1	.667			.618		
AIA2	.787				.867	
AIA1	.794				.848	
AIA3	.828				.844	
PEU1	.766					.823
PEU4	.732					.698
PEU3	.682					.587

*F= Factor

In Table 1, the factor loadings ranged between .72 and .81 in the first dimension (PU), .54 and .88 in the second dimension (SE), .62 and .75 in the third dimension (BI), .84 and .87 in the fourth dimension (AIA) and .59 and .82 in the fifth dimension (PEU). These values show that the acceptance level of the items is .55 and above. Cronbach's α values examined to reveal the reliability of the data. The Cronbach's α coefficient for the overall 18-item scale was found to be .836. This coefficient was calculated as .897 for the PU, .762 for the PEU, .860 for the SE, .867 for the AIA and .868 for the BI factor. Cronbach's α value between .60 and .90 means that the scale is highly reliable (Büyüköztürk, et al., 2018).

Data Analysis

In this study, SEM was used to evaluate and validate the proposed theoretical model. SEM is a statistical approach that explains the cause-and-effect relationship between observed and latent variables within hypotheses and can determine direct and indirect effects and standard errors between variables (Raykov and Marcoulides, 2000). The following steps were followed in the structural equation modeling method (Dursun & Kocagöz, 2010):

(1) A structural model was created to explain the hypotheses of the research. (2) The parameters of the model were defined and the observed variables belonging to the latent variables were

determined and the measurement model was defined. (3) The goodness of fit statistics of the model were examined. (4) The regression weights (estimates) and significance values of the relationships were examined and the model was analyzed. In this context, the measurement model was evaluated first and the structural model was tested in the next step. In the first step, reliability and convergent validity were calculated by examining the adequacy of fit. Finally, the seven hypotheses of the study were tested with Amos. Maximum Likelihood method was used to analyze data.

3. Result

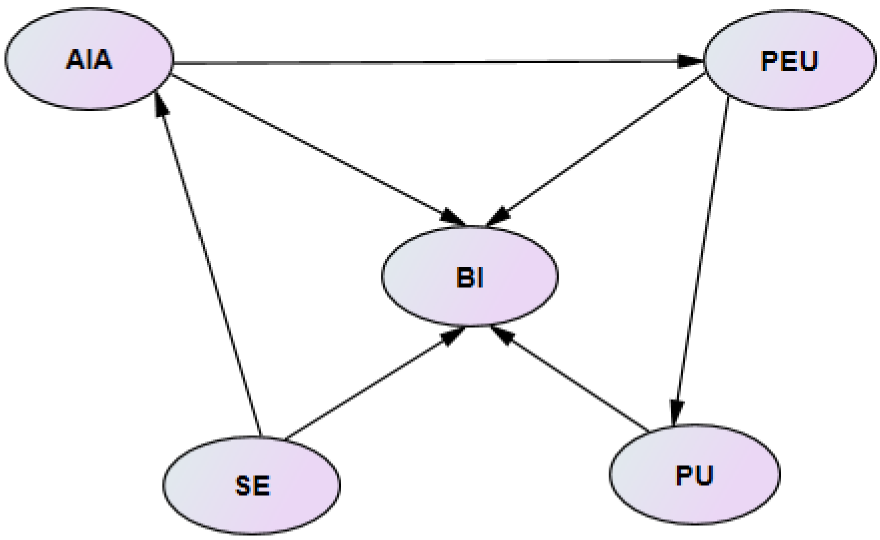
Text Testing the Measurement Model

Before testing the measurement model, the skewness and kurtosis values of the items were calculated to vary between -1.033 and .705 and -.931 and .951, respectively. These values were found to be within acceptable limits for the normality assumption (Büyüköztürk, 2014).

In this study, the CFA evaluation model (Structural model), which includes five constructs, namely PU, PEU, SE, AIA and BI, was applied (Figure 1).

Figure 1.

Structural Model



$\chi2$/df and TLI, CFI, NFI, RMSEA, SRMR fit indices were used for the fit evaluation of the model created with seven hypotheses. The $\chi2$/df value of the model is 2.067. This value is below the threshold of ≤ 3.0 defined by Schermelleh-Engel et al. In addition, the NFI, CFI and TLI values obtained in the study are 0.900, 0.945 and 0.933, respectively. All of these values exceed the 0.9 threshold specified by Hair et al. (2005) and Kline (2023). The RMSEA value is 0.079, which is below the threshold of <0.08 suggested by Hair et al. The values showed a good fit with the data set.

After determining that the values were acceptable, the standardized factor loadings of the items and the Cronbach's α, AVE and CR values of the dimensions were calculated (Table 2).

Table 2.

Values of Measurement Model

Factor	Item	Standardized Factor Loading
Self-efficacy (SE)	SE1	.777***
(α = .889; AVE= .672; CR= .891)	SE2	.854***
	SE3	.808***
	SE4	.840***
Artificial Intelligence Anxiety (AIA)	AIA1	.779***
(α = .856; AVE= .664; CR= .855)	AIA2	.752***
	AIA3	.906***
Perceived Ease of Use (PEU)	PEU1	.680***
(α = .818; AVE= .596; CR= .815)	PEU3	.815***
	PEU4	.815***
Perceived Usefulness (PU)	PU1	.864***
(α = .928; AVE= .767; CR= .929)	PU2	.904***
	PU3	.850***
	PU4	.886***
Behavioral Intention (BI)	BI1	.781***
(α = .918; AVE=.745; CR= .921)	BI2	.912***
	BI3	.863***
	BI4	.893***

***$p < 0.001$

In Table 2, factor loading values range between 0.680 and 0.912. Factor loadings are recommended to be above 0.50 (Hair et al., 2005). It is seen that the values obtained in Table 2 meet this threshold. The Cronbach's α values of the dimensions ranged between .818 and .928. Cronbach's α for the overall model was calculated as .841. These results show that the factor valuation has sufficient internal consistency.

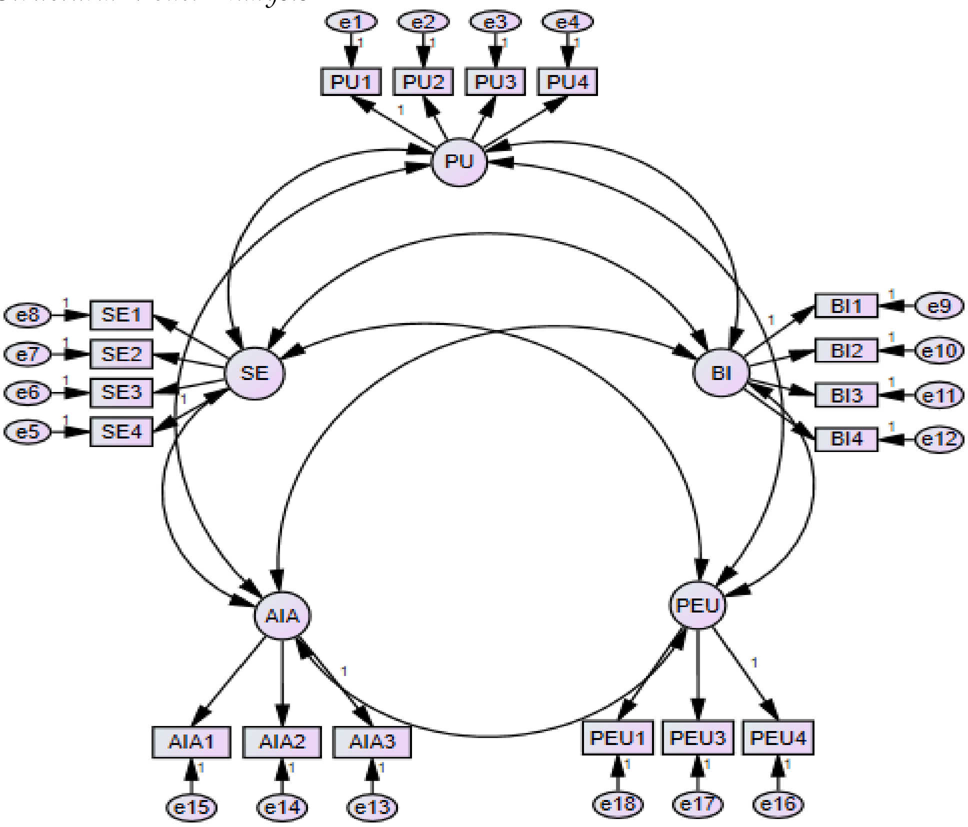
In addition, the convergent validity of the measurement model was assessed using two main indices. These are; Composite Reliability (CR) and Average Variance Explained (AVE). Fornell and Larcker (1981) suggested that AVE should exceed 0.5 and CR should exceed 0.7 for convergent validity. The values obtained in the measurement model are above these thresholds. This indicates that the current study has a good convergent validity for the variables used.

Structural Model

The structural model was evaluated after the measurement model. The hypothesized relationships of the model proposed in the study were established using SEM. Figure 2 shows a summary of the analysis of this model.

Figure 2.

Structural Model Analysis



The values and results calculated as a result of analyzing the model are given in Table 3.

Table 3.

Hypotheses and Results of the Model

Hypotheses	Path	β	S.e	*t*	*p*	Result
H1	SE - > AIA	-0.374	0.094	-4.426	***	Supported
H2	AIA - > PEU	-0.560	0.063	-6.569	***	Supported
H3	PEU - > PU	0.882	0.096	10.641	***	Supported
H4	SE - > BI	0.463	0.049	7.087	***	Supported
H5	PEU - > BI	0.126	0.143	-0.819	0.413	Not supported
H6	PU - > BI	0.575	0.117	3.952	***	Supported
H7	AIA - > BI	-0.270	0.047	-3.911	***	Supported

β = Standardized path coefficient ***: *P*< 0.001

Table 3 shows that six of the seven hypotheses are supported ($p< 0.001$) and only one (H5) is not supported. A significant negative effect of SE on AIA (β= -0.374); AIA on PEU (β= -0.560) and AIA on BI (β= -0.270) was found (H1, H2, H7). In addition, PEU had a significant positive effect on PU (β= 0.882); SE on BI (β= 0.463) and PU on BI (β= 0.575) (H3, H4, H6). the hypothesis that peu has a significant positive effect on bı (H5) was not supported (β= 0.126; p=0.413).

Standardized path coefficients less than |0.10| indicate a weak effect, close to |0.30| indicate a moderate effect, and greater than |0.50| indicate a strong effect (Cohen, 1992). In the structural model, the effect of PEU on PU was found to be the strongest positive effect (β= 0.882). This is followed by the effect of PU on BI (β= 0.575). The strongest negative effect is the effect of AIA on PEU (β= -0.560). The effects of SE on AIA (β= -0.374), SE on BI (β= 0.463) and AIA on BI (β= -0.270) are moderate. In addition, t values in path analyses are considered significant at 0.05 level if they are greater than |1.96| and at 0.01 level if they are greater than |2.56| (Hoyle, 1995). Therefore, the t values for the paths in hypotheses H1, H2, H3, H4, H6 and H7 can be accepted as significant at 0.01 level.

4. Discussion and Conclusion

This study examined the factors affecting the acceptability of AI technologies among teachers. Based on TAM, this study added "self-efficacy and anxiety" towards AI to investigate the factors affecting teachers' acceptance of AI technologies as well as their perspectives on AI-supported teaching. The findings of the study showed that teachers' PEU significantly positively influenced their AIA, SE significantly positively influenced their AIA, and AIA significantly positively influenced their AIA, supporting hypotheses H3, H4, and H6, respectively. In addition, teachers' SE significantly negatively affected their AIA, and AIA significantly negatively affected their PEU and BI, supporting hypotheses H1, H2 and H7, respectively. Hypothesis H5, which states that teachers' PEU positively affects their BI, was not supported. Thus, six of the seven proposed hypotheses were supported while only one was not supported.

The effect of teachers' PEU on their PU and then the effect of PU on BI were found to be the strongest positive effects in the model, respectively. These findings indicate that teachers believe that AI technologies that are easy to use in technology-assisted instruction are more likely to be useful. And it shows their belief that the usefulness of these technologies can make them willing to use them. These results are in line with the principles of the TAM theory (Davis et al., 1989). The positive effects of PEU on PU and the positive effects of PU on BI are consistent with the existing findings in studies in which artificial intelligence technologies are integrated into TAM (Choi et al., 2023; Ma and Lei, 2024; Naidoo, 2023; Wang et al., 2021; Zhang et al., 2023)

Findings demonstrate a strong negative effect of teachers' AIA on their PEU. In other words, when teachers' AI anxiety is low, they think that it is easy to use AI technologies in teaching. Zhang et al. (2023) reported that anxiety of female teachers about artificial intelligence was effective on PEU, but it was not effective in the male group. Venkatesh (2000) stated that anxiety is a belief that prevents the formation of a positive perception of ease of use.

This study confirmed the negative effect of teachers' SE on their AIA. This finding indicates that teachers with high self-efficacy have low anxiety about using AI technologies in teaching. In parallel with the current finding, Wang et al. (2021) emphasized in their study that university teachers' self-efficacy towards AI-based applications negatively affected their anxiety. In addition, Chatzoglou et al. (2009) indicated a positive relation between self-efficacy and computer anxiety in the model they created based on TAM.

The positive relation between teachers' SE and BI in this study is in line with Aktürk and Delen's (2020) finding. The current finding indicates that when teachers' self-efficacy towards artificial intelligence is high, intention to use this technology in teaching and therefore acceptance may also be high. Similarly, Çelik (2019) stated that instructors' self-efficacy to use augmented reality technology in teaching has a positive relation with their acceptance of this technology. Alenezi et al. (2010), Teo (2009) and Wong (2015) concluded that computer self-efficacy is good at predicting intent. Gurer (2020), on the other hand, highlighted that there wasn't direct effect between technology self-efficacy and behavioral intention. In addition, teachers' AIA significantly and negatively affected their BI. This result implies that teachers with high AI anxiety are less inclined to accept AI technology-supported instruction. Also it is similar to the findings of Alenezi et al. (2010) that computer anxiety significantly affects intentions to use technology. When we look at the other studies in which TAM was used, it was found that anxiety towards technology use negatively affected behavioral intention indirectly rather than directly (Akbıyık & Coşkun, 2013; Wang et al., 2021). Since AI technology in teaching is in its infancy, most teachers are still concerned about whether their computer and communication technology skills can meet the needs of integrating AI into teaching practice (Wang et al., 2021).

Contrary to expectations, there wasn't significant relation between teachers' PEU and BI. This explain that even if teachers perceive the use of artificial intelligence technologies as easy, this does not mean that they accept to use these technologies in teaching. Similar to the findings, there are studies that concluded participants' ease of use in integrating technologies into teaching is correlated with intent to use them (Al-Adwan et al., 2023; Naidoo, 2023; Wang et al., 2021). The current finding is not in line with the principles of the TAM theory. In line with this theory, Ma and Lei (2024) concluded that teacher education students' perceptions of the ease of use of artificial intelligence technologies have a significant effect on their intention to use them. Venkatesh (2000) found differences in the effects of external constructs across populations when evaluating the effect of external constructs on TAM. It is possible that the effects of the external constructs (self-efficacy and AI anxiety) examined in current research are not generalizable and can change depending on different technologies (Teo & Zhou, 2014).

To summarize, this study shows that the extended version of the TAM is effective in explaining teachers' acceptance of AI technology in technology-enhanced instruction. In addition, this research provided a basis for investigators to uncover the underlying reasons for the lack of acceptance towards AI technologies. Davis (1989) emphasizes that systems should be evaluated not only to predict acceptability but also to diagnose the causes of lack of acceptance and develop interventions to improve user acceptance. The fact that this study is the first TAM study on artificial intelligence technologies in Turkey makes it important and fills the gap in the literature. In addition, the results are valuable in terms of helping future educational planning in the use of educational technologies.

This study reveals the important role of self-efficacy towards AI and AI anxiety in teachers' acceptance of AI technology and lays the foundation for future researches in technology acceptance model theory. Future research can extend the TAM by adding sociocultural or psychological factors that influence teachers' acceptance of AI. It was found that there were significant effects between PEU and PU and between PU and BI. Therefore, the ease of use of AI technologies positively affects its usefulness and usefulness positively affects the intention to use it. This emphasizes the importance of focusing on the practical utility of a particular AI technology when evaluating whether it should be applied to teaching. That is, AI technology may improve the quality of instruction and allows teachers perform their tasks efficiently (Ma & Lei, 2024). Therefore, in-service trainings can be provided to teachers on the advantages of using AI technology in education. In addition, in this research, AIA has a significant effect on PEU. From the perspective of facilitating teachers' acceptance of AI technology, trainings can be designed and implemented that focuses the utility of AI technologies in education practices and reduce the anxiety they may cause (Wang, 2021).

The rapid progress and development of artificial intelligence technology may also change teachers' acceptance of using AI technology over time. In this context, the research can be repeated in the future and updates can be made. This research conducted with teachers can also be applied to prospective teachers. In this study, while determining the factors affecting teachers' acceptance of artificial intelligence technology, a model was created based on direct effects. The study can be expanded by considering indirect effects.

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