

Teachers' Artificial Intelligence Anxiety and Psychological Well-Being: The Mediating Role of Artificial Intelligence Self-Efficacy and Attitude

Burak Aydın

burakaydin@gumushane.edu.tr

Gümüşhane University

Yeşim Saruhan

Gümüşhane University

Uğur Saruhan

Gümüşhane University

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Abstract

The increasing use of artificial intelligence (AI)-based technologies in educational settings is redefining teachers' professional roles and creating new psychological demands. However, the mechanisms through which AI anxiety affects teachers' psychological well-being have not yet been sufficiently clarified. This study aims to examine the effect of teachers' AI anxiety on psychological well-being within the Job Demands–Resources (JD-R) model framework and to test the sequential mediating roles of AI self-efficacy and attitudes toward AI in this relationship.

The study was conducted with 432 teachers working in different school types (M age = 40.59, SD = 8.22). Data were collected using scales measuring AI anxiety, AI self-efficacy, AI attitude, and psychological well-being. The serial mediation model was tested using the PROCESS Macro (Model 6) with 5,000 bootstrap samples.

Findings revealed that AI anxiety was negatively related to psychological well-being. However, when mediating variables were included in the model, the direct effect of AI anxiety became insignificant, and the relationship was found to occur entirely through indirect effects. The total indirect effect of AI anxiety on psychological well-being is significant. Specifically, it was found that increased anxiety first weakens AI self-efficacy; decreased self-efficacy negatively affects attitudes toward AI, and this cognitive-emotional process leads to a decline in psychological well-being. The model explains 9.6% of the variance in psychological well-being.

These results show that AI-based technological transformation affects teacher well-being not directly, but through the erosion of individual resources and technological evaluation processes. The study contributes to the literature by extending the JD-R model in the context of artificial intelligence and reveals that interventions aimed at strengthening teachers' artificial intelligence self-efficacy and developing positive attitudes can play a critical role in supporting psychological well-being.

Introduction

In recent years, significant changes have occurred in educational environments regarding digitalization and the redefinition of teacher roles. In this process, it has been emphasized that teachers' well-being should be considered a critical priority for sustainable success and effective teaching in education [1]. Teachers' psychological well-being is considered a fundamental determinant for maintaining professional functionality and teaching quality in educational settings; as their psychological well-being levels directly affect their classroom interactions [2], teaching motivation [3], and professional commitment [4]. However, the structure of the teaching profession, shaped by multiple roles, increasing responsibilities, and changing expectations, can strain teachers' psychological resources [5]. Psychological well-being is a multidimensional construct defined by an individual's self-acceptance, ability to give meaning to their life, influence their environment, and pursue personal growth [6]). In this context, it is stated that teachers with high levels of psychological well-being cope more effectively with stress [7], are able to focus more on teaching processes [8]), and have increased quality of interaction

with students [9]. Conversely, teachers with low psychological well-being may struggle to cope with stress in teaching processes, experience a decline in teaching performance, and see their professional satisfaction levels negatively affected [10].

Today, the accelerating digital transformation in educational processes and, in particular, the proliferation of artificial intelligence-based technologies are significantly transforming teachers' professional roles and working practices. The integration of artificial intelligence applications into teaching processes requires teachers to have competencies beyond pedagogical knowledge and skills, such as adapting to new technologies and effectively using data-driven tools [11]. This transformation may bring psychological reactions such as uncertainty, decreased sense of control, and competence questioning for teachers [12]. In this respect, artificial intelligence can be considered not only as a technological innovation that supports teaching for teachers but also as a new source of stress and anxiety that can have negative effects on psychological well-being.

The Job Demands–Resources (JD-R) model suggests that employees' psychological well-being depends on the balance between the demands they encounter in the work environment and the individual and contextual resources they possess [13]. According to this model, job demands refer to elements that require constant effort from the employee and generate psychological costs, while job resources are defined as factors that reduce the negative effects of these demands, increase motivation, and support psychological well-being [14, 15]. In today's educational environments, artificial intelligence-based technologies can create new job demands for teachers, such as uncertainty, role change, and learning pressure [16]. When these demands are not balanced with sufficient psychological resources, they can negatively affect teachers' psychological well-being [17]. Within the framework of the JD-R model, teachers' perceptions of self-efficacy and attitudes toward artificial intelligence can be considered important individual resources that can reduce the effects of stress created by these new technological demands.

Artificial Intelligence Anxiety and Psychological Well-Being

Software used in education increasingly integrates AI-based technologies to help teachers more effectively support students' learning processes and improve academic performance [18]. The increasingly effective roles of artificial intelligence-based systems in education and teaching processes require teachers to reevaluate their professional responsibilities and perceptions of control over teaching; this leads to pedagogical decision-making processes being carried out in closer interaction with technology [19]. If this transformation process is not supported by sufficient information and resources or is not managed effectively, teachers may perceive artificial intelligence as a source of anxiety rather than a supportive tool [20]. AI anxiety refers to the negative emotional and cognitive responses that arise when individuals encounter or use AI-based systems, due to uncertainty, loss of control, and a perceived loss of competence [21].

AI anxiety among teachers may stem from the roles that AI-based systems assume in teaching and learning processes, which can undermine perceptions of pedagogical control and professional autonomy [22]. The lack of clarity regarding how the decision-making and guidance functions of artificial intelligence systems integrate with teachers' judgments may create cognitive uncertainty associated with a loss of control and a diminished sense of competence among teachers [23, 24]. In addition, low perceptions of technical and pedagogical competence regarding AI and limited effective professional support mechanisms may lead teachers to perceive these technologies as a difficult task to manage [17]. In this context, AI anxiety can be considered a risk factor that may affect not only teachers' attitudes toward technology but also their overall psychological functioning. Persistent uncertainty about artificial intelligence, loss of control, and declining perceived competence may create a job demand associated with increased cognitive load for teachers, straining their psychological resources [16]. The persistence of such demands may lead to increased stress levels among teachers, making it difficult for them to maintain emotional balance and negatively affecting their professional functioning [25]. Therefore, it can be said that teachers' psychological well-being levels will be lower in situations where AI anxiety is high; this relationship may be critically important for understanding the psychological consequences of technological transformation in education.

JD-R model suggests that employees' psychological well-being weakens as the continuity and intensity of the job demands they face increase, and that negative outcomes arise particularly when these demands are not balanced by sufficient individual or contextual resources [26]. In this context, AI anxiety can function as a job demand for teachers that involves uncertainty, loss of control, and cognitive load; the persistence of this demand can negatively affect psychological well-being by depleting teachers' psychological resources [27]. Therefore, in line with the JD-R model, it can be said that a decrease in teachers' psychological well-being levels in situations where AI anxiety is high is a theoretically expected outcome.

Artificial Intelligence Self-Efficacy and Artificial Intelligence Attitude as Mediators

Artificial intelligence self-efficacy refers to individuals' perceptions of how competent they are in learning, using, and overcoming difficulties they may encounter with AI-based tools [28]. When these beliefs are high, AI-based tools can be perceived as more manageable, predictable, and functional [29]. Indeed, research shows that self-efficacy plays a decisive role in the adoption of new and complex technologies such as artificial intelligence [30, 31]. For example, according to Chen et al. [32] individuals with high AI self-efficacy may have stronger beliefs about their own capacities and competencies regarding these technologies; this can increase their openness to learning and motivation. AI self-efficacy can also directly influence teachers' assessments and attitudes toward AI [33]. This is because teachers who are confident in using artificial intelligence tools are more likely to believe that these technologies are supportive and beneficial to the teaching process, while teachers with low self-efficacy may perceive artificial intelligence as complex, challenging, and threatening [33]. In this regard, AI self-

efficacy may emerge as a key determinant in teachers' development of positive or negative attitudes toward AI [34, 35]. Teachers' attitudes toward artificial intelligence may influence their psychological experiences and overall well-being during the process of interacting with these technologies [25]. Negative attitudes toward artificial intelligence may make it difficult for teachers to maintain emotional balance by causing them to perceive technological demands as more stressful and threatening. In contrast, teachers who view artificial intelligence as a supportive and functional tool may respond more adaptively to the technological change process [36].

Teachers' increased exposure to and necessity to use AI-based tools (in lesson planning, assessment, content creation, administrative tasks, or professional decision-making processes) may lead them to experience greater uncertainty and difficulty related to these technologies [37, 38]. These experiences may undermine teachers' confidence in their ability to use AI tools effectively, causing them to feel less competent in relation to these technologies [33]. Declining AI self-efficacy may reshape teachers' assessments of AI, paving the way for negative attitudes about whether these technologies are useful, supportive, and functional [39]. Teachers who view AI as a complex, challenging, or threatening element rather than an opportunity to support teaching processes may experience the technological transformation process as more stressful and struggle to maintain emotional balance during this process [25]. These negative attitudes can create significant pressure on psychological well-being by weakening teachers' perceptions of professional competence, future expectations, and meaning in their lives [40]. In this context, it can be said that the effect of AI anxiety on teachers' psychological well-being is shaped through AI self-efficacy and AI attitude. In other words, AI anxiety may first weaken teachers' AI self-efficacy, then negatively affect their attitudes toward AI, and ultimately lead to a decrease in psychological well-being.

From the perspective of the JD-R model, the psychological consequences of the demands that AI-based technologies create for teachers can often be shaped through indirect and gradual processes [16, 41]. In particular, uncertainty, learning pressure, and changes in the perception of control can weaken teachers' perceptions of self-efficacy in coping with these technologies (Oran, 2025) [30]. This decline in self-efficacy perceptions may influence teachers' evaluations of artificial intelligence, paving the way for these technologies to be perceived as useful, supportive, or threatening [35]. In this context, attitudes toward artificial intelligence may emerge as an important cognitive evaluation process that shapes the relationship between increasing demands and psychological outcomes. As predicted by the JD-R model, the gradual depletion of individual resources and the more negative interpretation of demands may lead to damage to teachers' psychological well-being. In this framework, it can be said that the effect of AI anxiety on psychological well-being occurs through a sequential mechanism via AI self-efficacy and attitudes toward AI.

Current Study

The proliferation of artificial intelligence-based applications in educational settings necessitates a closer examination of the psychological dimensions of teachers' relationship with these technologies [25]. The

integration of artificial intelligence systems into teaching processes can cause teachers to encounter perceptions of uncertainty, loss of control, and threats to professional competence; this situation paves the way for the emergence of artificial intelligence anxiety [22]. Current literature has focused on teachers' perceptions of AI, their levels of acceptance, their intentions to use it, and pedagogical integration processes; in contrast, research explaining the effect of AI anxiety on teachers' overall psychological well-being has been limited.

It can be argued that the psychological consequences of AI anxiety do not emerge directly and automatically; rather, they are shaped through an individual's personal resources and cognitive evaluation processes [15, 42]. At this point, artificial intelligence self-efficacy may emerge as a fundamental individual resource representing teachers' beliefs that they can cope with these technologies. Increased anxiety levels may undermine teachers' confidence in their ability to use these technologies effectively. Decreased perceptions of self-efficacy may then lead to a reshaping of evaluations of artificial intelligence, influencing attitudes toward whether the technology is beneficial or threatening. This evaluation process determines how teachers interpret technological change and may ultimately have an indirect effect on psychological well-being. Accordingly, this study aims to examine the effect of AI anxiety on teachers' psychological well-being within the framework of the JD-R model, with AI self-efficacy and AI attitude playing sequential mediating roles. The proposed model assumes that anxiety first weakens an individual's resources, then negatively affects technological evaluations, and that this process has an indirect effect on psychological well-being. The research hypotheses are formulated as follows:

H₁: There is a negative relationship between teachers' psychological well-being and AI anxiety.

H₂: Artificial intelligence self-efficacy and artificial intelligence attitude sequentially mediate the relationship between teachers' psychological well-being and artificial intelligence anxiety.

Method Participants

The current study was conducted using convenience sampling, including teachers who are actively working. During the data collection process, the researchers visited various schools to provide information about the purpose of the study, then sent teachers a link to an online survey prepared using Google Forms via WhatsApp. Only teachers who voluntarily agreed to participate in the study were included.

The G*Power 3.1 program was used to determine the sample size and power. A minimum sample size of 359 was calculated for models with an effect size (F^2) = 0.04, alpha level 0.05, and power level 0.95. Considering possible data loss, the researchers administered the scales to 455 individuals. Twenty-three survey data sets that were observed to be outliers and distorted the normality were excluded. Analyses were performed on 432 data sets.

Participants' ages ranged from 24 to 64, with an average age of 40.59 (SD = 8.22). Of the participants, 240 (55.6%) were female and 192 (44.4%) were male. Participants' professional seniority ranged from 1 to 40 years, with an average seniority of 16.22 years (SD = 8.66). Participants also worked in different types of schools: 39 (9.0%) work in preschool, 93 (21.5%) in elementary school, 112 (25.9%) in middle school, 148 (34.3%) in high school, and 40 (9.3%) in special education, guidance, and research centers.

1. Artificial intelligence anxiety scale: Participants' levels of concern about artificial intelligence were determined using the scale developed by Akkaya et al. [21]. This scale consists of 16 items (e.g., "Learning to use artificial intelligence techniques makes me anxious," "I am learning to use human-like artificial intelligence techniques"). Items are rated on a scale from "1 = strongly disagree" to "5 = strongly agree." The scale is used to calculate the total score. Higher scores on the scale indicate higher artificial intelligence anxiety. The validity of the scale was tested using confirmatory factor analysis. The results confirmed the factor structure of the scale ($\chi^2 = 2.63$, RMSEA = 0.078, NFI = 0.92, IFI = 0.95, CFI = 0.95). The overall Cronbach's alpha internal consistency coefficient of the scale is 0.94. The internal consistency coefficients of the subscales ranged from 0.87 to 0.95. In this study, we calculated Cronbach's alpha as 0.92 for the scale as a whole.

2. Artificial intelligence self-efficacy scale short form: The five-item 'Technology Self-Efficacy Scale' developed by Montag et al. [43] was used to determine individuals' perceived levels of self-efficacy in using artificial intelligence technologies. The scale adaptation process into Turkish was conducted by Türk et al. [28]. During the adaptation process, the term "technology" in the scale items was adapted to "artificial intelligence technologies/products" in line with the purpose of the study. Participants responded to items such as "I am not confident in my ability to use artificial intelligence technologies/products" on a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). Items 2, 3, and 5 were reverse-coded. Higher scores on the scale indicate higher artificial intelligence self-efficacy. As part of the adaptation study, the internal consistency of the scale was assessed using Cronbach's alpha coefficient ($\alpha = .77$) and McDonald's omega coefficient ($\omega = .79$). Furthermore, the results of the confirmatory factor analysis revealed that the scale's single-factor structure showed an acceptable level of fit with the data ($\chi^2/\text{df} = 3.28$, RMSEA = .08, CFI = .94, TLI = .86). In this study, the Cronbach's alpha internal consistency coefficient of the scale is 0.80.

3. Artificial intelligence (AI) attitude scales (AIAS-4): AIAS-4 was developed by Grassini [44] to measure attitudes toward artificial intelligence technology and was adapted into Turkish by Satıcı et al. [36]. The scale consists of four items (e.g., "I believe artificial intelligence will improve my work") on a 10-point scale ranging from 4 to 40 (1 = strongly disagree; 10 = strongly agree). There are no reverse items. A higher total scale score indicates a more positive attitude toward artificial intelligence. Confirmatory factor analysis results revealed that the scale's unidimensional structure fit the data well (CFI = .99, GFI = .99, NFI = .99, TLI = .97, SRMR = .02). As part of the adaptation study, the internal consistency of the scale is Cronbach's alpha coefficient $\alpha = 0.86$. In this study, we calculated Cronbach's alpha as 0.91.

4. Psychological well-being scale: In the study, the "Psychological Well-Being Scale" developed by Diener et al. [45] and adapted into Turkish by Telef [46] was used to determine individuals' levels of psychological well-being. The scale (strongly disagree = 1; strongly agree = 7) consists of eight items

(e.g., "I lead a purposeful and meaningful life," "I am competent and adequate in activities that are important to me"). All items are phrased positively. Higher scale scores are interpreted as increased psychological well-being. Exploratory factor analysis (EFA) revealed that the scale explained 42% of the total variance. The findings reveal that the scale has a single-factor structure, as in its original form. Item factor loadings were found to range between .54 and .76. Confirmatory factor analysis showed that the model fit was acceptable, with fit indices of $\chi^2/df = 4.645$ (92.90/20), RMSEA = .08, SRMR = .04, GFI = .96, NFI = .94, RFI = .92, CFI = .95, and IFI = .95. In this study, we calculated Cronbach's alpha as 0.80 for the scale as a whole.

Data Collection Process:

Data were collected online from teachers actively working in various educational institutions in Turkey between December and January. The necessary ethical committee approval was obtained for the research. Participation in the research was voluntary. Participants were informed about the purpose of the research and the principles of confidentiality, and their informed consent was obtained electronically on a voluntary basis. The scales were administered online, and it took approximately 10 minutes to complete the questionnaire.

Data analysis:

In the first stage, we calculated the relationships between AI anxiety, AI self-efficacy, AI attitude, and psychological well-being. In the second stage, regression analysis revealed the extent to which AI anxiety, AI self-efficacy, and AI attitude predicted psychological well-being. In the third stage, the indirect effect of AI anxiety on psychological well-being was determined through AI self-efficacy and AI attitude. In the final stage, bootstrap confidence intervals were used to determine the significance of the indirect effects [47]. The mediation model of the study was conducted using the PROCESS macro (Model 6). Indirect effects were calculated using 5000 bootstrap resamples and a 95% confidence interval [48]. SPSS version 27 was used for all analyses.

Findings Preliminary Analysis

Table 1 shows the correlation values between the variables in our study and the data regarding the normality distribution. The results indicate a low level of positive and significant relationship between artificial intelligence self-efficacy and psychological well-being ($r = .27, p < .01$). While AI anxiety was negatively and weakly correlated with psychological well-being ($r = -.18, p < .01$), a positive and weakly significant relationship was found between AI attitude and psychological well-being ($r = .24, p < .01$). Furthermore, moderate negative correlations were observed between AI anxiety and AI self-efficacy ($r = -.36, p < .01$) and AI attitude ($r = -.54, p < .01$). Furthermore, Table 1 shows that the skewness and kurtosis values of all variables remained within the ± 1 limits. These values indicate that the data meet the necessary criteria for the normality assumption [49].

When the correlation results are evaluated within the framework of the JD-R Theory, it is seen that anxiety negatively affects psychological well-being as a job demand; however, individual resources such as self-efficacy and attitude mitigate this negative effect and indirectly increase psychological well-being. This relational structure theoretically and empirically supports testing the serial mediation model, which predicts that anxiety's effect on psychological well-being operates through self-efficacy and attitude.

Table 1
Descriptive statistics and correlations between variables

Variables	1	2	3	4
1. Artificial intelligence self-efficacy	—			
2. Artificial intelligence anxiety	– .36*	—		
3. Attitudes toward artificial intelligence	.37*	– .54*	—	
4. Psychological well-being	.27*	– .18*	.24*	—
M	4.74	2.92	6.70	5.75
Sd	1.16	0.71	1.99	2.92
Skewness	-0.11	-0.28	-0.54	-0.62
Kurtosis	-0.59	0.10	0.18	0.43
Note: *p < .001.				

Mediation analysis

It was tested whether artificial intelligence self-efficacy and attitudes toward artificial intelligence sequentially mediated the relationship between artificial intelligence anxiety and psychological well-being. The analysis results are presented in Fig. 1 and Table 2.

Figure 1 shows that AI anxiety among teachers significantly and negatively predicted AI self-efficacy ($\beta = -.36$, $p < .001$). Similarly, AI anxiety also significantly and negatively predicted attitudes toward AI ($\beta = -.47$, $p < .001$). Furthermore, AI self-efficacy significantly and positively predicted attitudes toward AI ($\beta = .20$, $p < .001$). In terms of psychological well-being, AI self-efficacy was found to significantly and positively predict psychological well-being ($\beta = .21$, $p < .001$). Similarly, attitudes toward artificial intelligence also have a positive and significant effect on psychological well-being ($\beta = .15$, $p = .010$). However, when the mediating variables were included in the model, the direct effect of artificial intelligence anxiety on psychological well-being was no longer significant ($\beta = -.02$, $p = .692$). However, the total effect is significant and negative ($\beta = -.18$, $p < .001$). The model explained 9.6% of the variance in teachers' psychological well-being.

The bootstrap analysis results in Table 2 showed that the total indirect effect of AI anxiety on psychological well-being among teachers was significant ($\beta = -.154$, 95% CI = $-.2272, -.0821$). When examining specific indirect effects, the effect was significant both through AI self-efficacy ($\beta = -.076$, 95% CI = $-.1210, -.0357$) and through attitudes toward AI ($\beta = -.068$, 95% CI = $-.1288, -.0073$) and through the sequential effect of self-efficacy and attitudes ($\beta =$

$-.010$, 95% CI = $-.0222, -.0011$). These findings indicate that the effect of teachers' AI anxiety on their psychological well-being is not direct but indirect, mediated by AI self-efficacy and attitudes toward AI.

Table 2
Bootstrapped indirect effects

Variable	β	SE	95% CI	
			Lower	Upper
Total Indirect Effect	-.154	.04	-.2272	-.0821
AIA $\rightarrow$ AISE $\rightarrow$ PWB	-.076	.02	-.1210	-.0357
AIA $\rightarrow$ AIAtt $\rightarrow$ PWB	-.068	.03	-.1288	-.0073
AIA $\rightarrow$ AISE $\rightarrow$ AIAtt $\rightarrow$ PWB	-.010	.01	-.0222	-.0011
<i>Note. N = 432. Values are standardized indirect effects (β). AIA = Artificial Intelligence Anxiety; AISE = Artificial Intelligence Self-Efficacy; AIAtt = Attitudes Toward Artificial Intelligence; SWB = Psychological Well-Being; CI = Confidence Interval</i>				

Discussion

In this study, based on the JD-R model, the effect of teachers' artificial intelligence anxiety on psychological well-being and the sequential mediating role of artificial intelligence self-efficacy and attitudes toward artificial intelligence in this relationship were examined. The findings support the proposed model.

In line with the first hypothesis of the study, a significant negative relationship was found between AI anxiety and psychological well-being. This finding reveals that AI anxiety acts as a risk factor that weakens psychological well-being among teachers. When evaluated within the JD-R model framework, it can be said that artificial intelligence anxiety strains teachers' psychological resources as a job demand involving uncertainty, loss of control, and cognitive load [16, 50]. This finding is consistent with recent studies showing that AI-related anxiety negatively affects teachers' professional well-being [25, 51, 52]. The proliferation of AI-based technologies in educational settings demands new technical competencies from teachers beyond pedagogical knowledge, which may lead to uncertainty in professional roles [53–55]. In this uncertain environment, teachers' weakened sense of control and increased competence concerns, along with heightened anxiety levels, may negatively affect psychological well-being. However, the most noteworthy aspect of this study is that it reveals this relationship occurs through indirect

mechanisms rather than direct ones. When mediating variables were included in the model, the direct effect of AI anxiety on psychological well-being became insignificant. This finding indicates that anxiety does not automatically and unconditionally reduce psychological well-being. On the contrary, it shows that this effect is shaped through the resources and cognitive evaluation processes possessed by the individual. This result is consistent with the JD-R model's fundamental prediction that job demands affect psychological outcomes not directly but through individual resources [42, 56].

The sequential mediation model tested under the second hypothesis of the study was found to be significant. All three indirect paths are statistically significant. In the first path, it was determined that AI anxiety negatively affects psychological well-being by weakening self-efficacy. This finding shows that anxiety undermines teachers' confidence in their ability to effectively use AI tools and that this loss of confidence directly weakens psychological well-being. Indeed, the perception of self-efficacy reflects individuals' beliefs about their capacity to cope with challenging situations, and strong beliefs increase psychological resilience [57, 58]. Teachers with high artificial intelligence anxiety may perceive these technologies as complex and difficult to manage. This perception can weaken self-efficacy beliefs and negatively affect psychological well-being.

The second indirect pathway in the study revealed that AI anxiety directly reduces psychological well-being by negatively influencing attitudes toward AI. This result shows that teachers with high anxiety levels perceive AI as a threatening element rather than a supportive tool, and this negative perception puts pressure on psychological well-being. Negative attitudes toward artificial intelligence may cause teachers to experience the technological transformation process as more stressful and to feel uncertainty about their professional future [59]. When evaluated from the JD-R model perspective, negative attitudes can be said to contribute to the perception of technological demands as more burdensome, leading to insufficient resources and weakened psychological well-being [60, 61].

The third and theoretically most critical indirect pathway in the study is the sequential mediation of AI self-efficacy and attitudes toward AI. In this pathway, AI anxiety first reduced self-efficacy, reduced self-efficacy negatively affected attitudes toward AI, and these negative attitudes led to a decline in psychological well-being. This sequential mechanism demonstrates that the psychological consequences of anxiety are not simple and linear. Instead, the process occurs as a cyclical sequence of stages that continuously feed into each other. This finding empirically supports the JD-R model's theoretical assumption that job demands progressively deplete individual resources, leading to negative outcomes [60, 62]. The AI anxiety observed in teachers initially undermines their sense of trust in the use of this technology. This loss of trust then leads to a gradual shift in general assessments of AI's usefulness toward the negative, thereby lowering psychological well-being levels. Indeed, the decisive effect of self-efficacy on attitudes is consistent with current studies in this field [54, 63, 64].

The fact that the research model explains 9.6% of the variance in psychological well-being indicates that the explained variance is relatively low. However, considering that psychological well-being is a multidimensional construct shaped by numerous individual and contextual variables such as personality

traits, social support, job satisfaction, and professional autonomy, this can be regarded as an expected result [65–67]. Nevertheless, the fact that AI anxiety has such a meaningful indirect effect on such a broad construct demonstrates that the technological transformation process has a significance that cannot be overlooked in terms of teachers' psychological functioning.

Recommendations

The findings of this study reveal that the negative effect of teachers' AI anxiety on psychological well-being occurs not directly but through individual resources such as self-efficacy and attitudes. These results bring some recommendations for educational policy and practice.

First, it is recommended that practice-oriented professional development programs be organized to improve teachers' skills in recognizing, using, and integrating artificial intelligence tools into teaching processes. Such programs can mitigate the negative effects of anxiety by strengthening teachers' perceptions of artificial intelligence self-efficacy. Including workshops and peer-supported learning processes that offer teachers the opportunity to experience AI tools in a safe environment, beyond the transfer of theoretical knowledge, may be more effective in developing self-efficacy. Furthermore, developing positive attitudes towards AI is also emerging as a critical area of intervention. It is important for school administrators and education policymakers to position artificial intelligence technologies not as a threat that replaces the teaching profession, but as a tool that supports teaching processes. In this regard, sharing concrete and successful examples of how artificial intelligence can be used effectively in the classroom can positively shape teachers' assessments of these technologies.

Finally, it is recommended that school counselors and administrators be aware of the anxiety and uncertainty teachers may experience during the technological transformation process and create a supportive organizational climate. Providing teachers with sufficient time, resources, and guidance can reduce the psychological costs of technological change and contribute to maintaining their well-being.

Limitations and future studies

Some limitations should be considered when evaluating the results of this study. First, as the research has a cross-sectional design, it is not possible to interpret the relationships between variables causally. Longitudinal studies are needed to confirm the temporal constraints of the proposed sequential mechanism from AI anxiety to self-efficacy, attitude, and psychological well-being. Second, the data were collected using self-report scales. Measurements based on self-report methods may carry limitations such as social desirability bias and common method variance. In future studies, the validity of the findings can be strengthened with mixed-design research supported by observation, interviews, or experimental methods. Third, the fact that participants reached through convenience sampling are limited to a specific geographic region and school type restricts the generalizability of the findings. Future studies are recommended to work with larger, more representative samples from different regions and school levels.

Fourth, the model explaining 9.6% of the variance in psychological well-being indicates that other important variables affecting this construct exist. Future research could contribute to a more comprehensive understanding of AI's impact on psychological well-being by including variables such as personality traits, social support, professional autonomy, school climate, and job satisfaction in the model. Finally, this study addressed AI anxiety as a general construct. However, it is thought that teachers' anxiety experiences may stem from different dimensions, such as job security, loss of pedagogical control, and concerns about technical competence. Future studies that examine the effects of these different dimensions of anxiety on psychological well-being separately may contribute more detailed insights to the field. Furthermore, comparative studies conducted in different cultural contexts and with different professional groups could provide an opportunity to test the generalizability of the proposed model.

Abbreviations

AI

Artificial intelligence

JD-R

Job Demands–Resources

SPSS

Statistical Package for the Social Sciences

χ^2

Chi-square

df

Degree of freedom

RMSEA

Root Mean Square Error of Approximation

SRMR

Standardized Root Mean Square Residual

GFI

Goodness of Fit Index

NFI

Normed Fit Index

RFI

Relative Fit Index

TLI

Tucker-Lewis Index

CFI

Comparative Fit Index

IFI

Incremental Fit Index

n.s.

Not significant

β

Values are standardized indirect effects

AIA

Artificial Intelligence Anxiety

AISE

Artificial Intelligence Self-Efficacy

AIAtt

Attitudes Toward Artificial Intelligence

SWB

Psychological Well-Being

CI

Confidence Interval

M

Mean

Sd

Standard Deviation

SE

Standard Error

Declarations

Ethics approval and consent to participate

This study was conducted in accordance with the Declaration of Helsinki and its later amendments. The study received approval from the Scientific Research and Publication Ethics Committee of Gümüşhane University (Approval No: 2025/7; Date: 26 September 2025). Participants received written information about the study and provided written informed consent prior to participation.

Consent to Publication

Not applicable.

Data availability

Data supporting the findings of this study can be obtained from the author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflict of interest.

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Author Contributions Statement

Burak Aydın developed the research design, conceptualized the study, revised the final version of the manuscript, and supervised the writing process.

Yeşim Saruhan conducted the literature review, prepared the initial draft of the manuscript, and contributed to the interpretation of the findings.

Uğur Saruhan managed the data collection process and performed the statistical analyses.

All authors read and approved the final version of the manuscript and agree to be accountable for the accuracy and integrity of its content.

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Figures

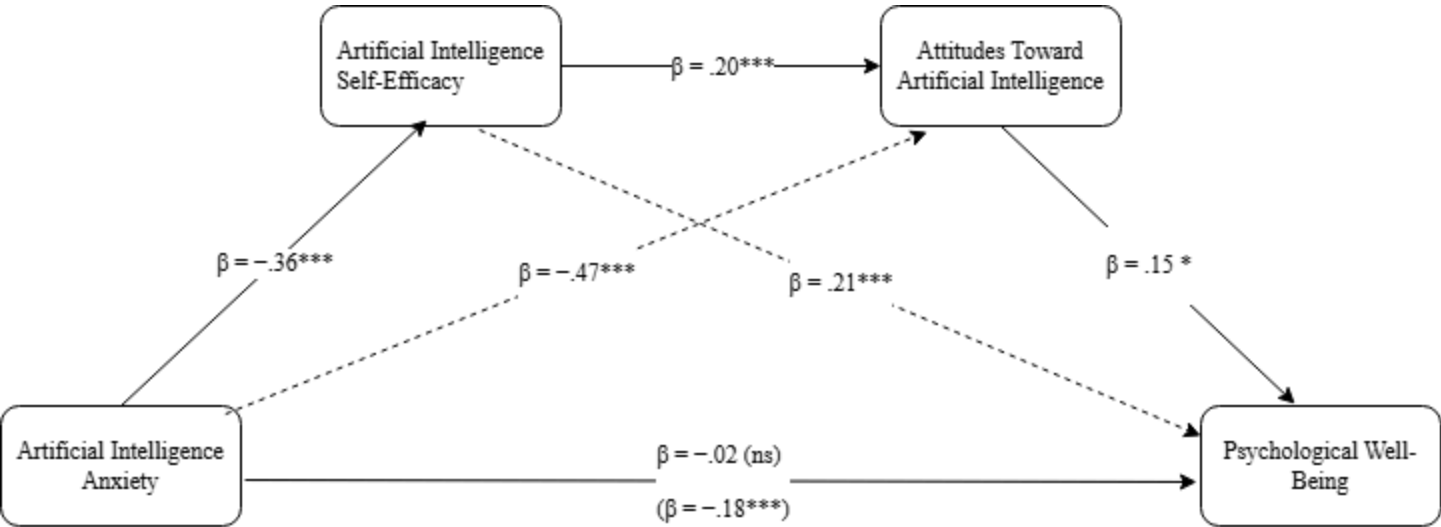


Figure 1. Mediation model depicting the associations among the study variables. *Notes.* N = 432. Values are standardized coefficients (β). The value in parentheses on the X $\rightarrow$ Y path represents the total effect. * $p < .05$, *** $p < .001$. ns = non-significant.

Figure 1

See image above for figure legend