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Explainable AI Modeling of Special Education Teachers' Psychological Well-Being During Artificial Intelligence Integration: The Roles of Occupational Stress, Self-Regulation, and Technological Confidence

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A B S T R A C T

Objective: This study aimed to develop an explainable artificial intelligence model for predicting psychological well-being among special education teachers during artificial intelligence integration by examining the roles of occupational stress, self-regulation, and technological confidence.

Methods and Materials: This quantitative, cross-sectional, predictive-correlational study was conducted among 318 special education teachers working in public and non-public exceptional schools in Tehran during the 2025–2026 academic year. Participants were selected through multistage cluster sampling. Data were collected using a demographic and professional information form, the Ryff Psychological Well-Being Scale, the Teacher Stress Inventory, the Short Self-Regulation Questionnaire, and the Computer Self-Efficacy Scale adapted to educational technology and artificial intelligence contexts. Data analysis included descriptive statistics, Pearson correlation, multiple linear regression, and supervised machine-learning modeling. Five predictive models were compared, including multiple linear regression, support vector regression, random forest regression, gradient boosting regression, and extreme gradient boosting regression. SHAP analysis was used to interpret feature importance and explain the final artificial intelligence model.

Findings: Psychological well-being was significantly and negatively correlated with occupational stress and significantly and positively correlated with self-regulation and technological confidence. The multiple regression model was significant, $F(6, 311) = 73.71$, $p < 0.001$, and explained 58.7% of the variance in psychological well-being. Self-regulation was the strongest positive predictor, followed by occupational stress as a negative predictor and technological confidence as a positive predictor. Frequency of AI-supported tool use also significantly predicted psychological well-being, whereas teaching experience and educational level were not significant predictors. Among the machine-learning models, extreme gradient boosting showed the best performance, with the highest test R^2 of 0.73 and the lowest prediction error. SHAP analysis identified occupational stress, self-regulation, and technological confidence as the most influential features in the final model.

Conclusion: The findings indicate that special education teachers' psychological well-being during artificial intelligence integration is primarily shaped by occupational stress, self-regulatory capacity, and technological confidence. Explainable artificial intelligence can provide an interpretable and practical framework for identifying psychological and technological factors that support teacher well-being.

Keywords: *Explainable artificial intelligence; psychological well-being; special education teachers; occupational stress; self-regulation; technological confidence; artificial intelligence integration.*

1. Introduction

Special education systems have increasingly evolved toward inclusive, technology-enhanced, and competency-driven frameworks that aim to ensure equitable learning opportunities for students with diverse learning needs. In this context, special education teachers occupy a central role in translating policy into practice, mediating between institutional expectations and individualized student requirements. Contemporary research highlights that these teachers are not only instructional agents but also emotional, behavioral, and organizational anchors within inclusive education systems (Ang & Spencer, 2022; Clausen et al., 2022; Howerter et al., 2022). The complexity of their professional responsibilities has intensified in recent years due to expanded inclusion mandates, increasing classroom heterogeneity, and rising expectations for individualized instruction and collaborative engagement with families and multidisciplinary teams (Ciocon, 2023; Gonzaga, 2024; Moon, 2023). Moreover, the role of school leadership and institutional structures has been identified as a significant determinant of successful special education implementation, particularly in fostering instructional readiness and program sustainability (Ang & Spencer, 2022; Ciocon, 2023).

In addition to structural demands, special education teachers frequently face substantial occupational and psychological burdens. Burnout, emotional exhaustion, and chronic occupational stress have been widely documented as persistent challenges in this profession (Brunsting et al., 2025; Cuadra, 2023; Esternon et al., 2023). These stressors are often compounded by the emotional demands of working with learners with complex disabilities, managing behavioral difficulties, and responding to high parental expectations (Lariba, 2023; Luisa & Tuvida, 2023; Villareal et al., 2022). The sandwich generation phenomenon further exacerbates these pressures, as many teachers simultaneously manage professional responsibilities and family caregiving roles, increasing emotional strain and reducing psychological resilience (Cuadra, 2023). Empirical evidence also indicates that external crises such as the COVID-19 pandemic have significantly intensified teacher stress, instructional instability, and professional uncertainty in special education settings (Camp et al., 2024; Esternon et al., 2023; Mwamakula, 2024).

Alongside stress-related challenges, the professional identity of special education teachers is increasingly shaped by technological transformation and digital integration in education systems. The rapid emergence of artificial intelligence and automated instructional tools has redefined teaching practices, requiring educators to adapt to new digital ecosystems and instructional paradigms (Dodur, 2025; Sallin, 2021; Wilson et al., 2024). AI-based educational systems are progressively being integrated into assessment, individualized instruction, and learning analytics, creating both opportunities and psychological challenges for teachers. While such technologies can enhance instructional efficiency and personalization, they also introduce cognitive overload, ethical concerns, and anxiety related to technological adaptation (Dodur, 2025; Wilson et al., 2024). Research suggests that teachers' attitudes toward artificial intelligence are significantly influenced by AI literacy and AI-related anxiety, which in turn affect their willingness to engage with digital tools in educational contexts (Dodur, 2025). Furthermore, machine learning and text-based analytics have begun to influence educational decision-making processes, reinforcing the need for teachers to develop higher levels of technological competence and digital adaptability (Sallin, 2021).

In response to these evolving demands, psychological and behavioral constructs such as self-regulation, technological confidence, and professional competence have gained increasing attention in educational research. Self-regulation, defined as the ability to manage cognitive, emotional, and behavioral processes toward goal-directed action, has been identified as a key protective factor in managing occupational stress and maintaining psychological stability among teachers (Hugh et al., 2023; Robinson et al., 2023). Effective self-regulation enables teachers to adapt instructional strategies, manage classroom challenges, and maintain emotional equilibrium under pressure. Similarly, technological confidence, or the perceived ability to effectively use digital tools, plays a critical role in facilitating successful adaptation to AI-enhanced educational environments (Dodur, 2025; Wilson et al., 2024). Teachers with higher technological confidence are more likely to engage with innovative instructional tools, experiment with adaptive learning systems, and integrate technology into pedagogical practice.

Professional development interventions such as lesson study, structured training programs, and collaborative learning models have been shown to enhance teaching competencies and instructional confidence in special education contexts (Basister et al., 2025; Cruz & Baguio, 2024; Hugh et al., 2023). These interventions not only strengthen pedagogical skills but also enhance teachers' adaptive capacity in dealing with classroom diversity and technological integration. Additionally, multi-tiered support systems and professional collaboration frameworks have been recognized as effective mechanisms for improving instructional quality and supporting evidence-based practice in inclusive education (Robinson et al., 2023). The importance of training mechanisms that support evidence-based practices has also been emphasized in relation to teachers of autistic learners, highlighting the need for continuous professional learning and structured instructional support (Hugh et al., 2023).

Beyond individual competencies, systemic and environmental factors significantly shape the experiences of special education teachers. Parental involvement, school-home partnerships, and institutional collaboration have been identified as essential components in improving educational outcomes for students with special needs (Ang & Spencer, 2022; Custodio et al., 2024; Tenerife et al., 2023). These collaborative structures reduce instructional burden on teachers and contribute to a more supportive educational ecosystem. However, challenges in inclusive education implementation remain persistent, particularly in terms of teacher readiness, resource allocation, and behavioral management in classroom settings (Bongabong et al., 2022; Gonzaga, 2024; Nah & Neo, 2022). Behavioral rigidity in students with autism spectrum disorder, for instance, can influence teacher perceptions of readiness and increase instructional complexity (Nah & Neo, 2022).

Instructional innovation and adaptive pedagogical strategies have also been highlighted as important contributors to teacher effectiveness in special education contexts. The use of arts-based instruction, mentoring systems, and specialized teaching tools has been shown to improve engagement and learning outcomes among students with disabilities (Caballero et al., 2023; Ortogero et al., 2022). Similarly, the development of structured instructional materials such as adaptive learning tools reflects ongoing efforts to improve teaching effectiveness and reduce cognitive load in complex educational environments (Jose Kim et al., 2024). These innovations demonstrate the growing intersection between pedagogy, technology, and cognitive science in special education.

Despite the growing body of literature addressing teacher stress, technological adaptation, and instructional innovation, several gaps remain. First, most existing studies have examined these constructs independently rather than in an integrated predictive framework. Second, limited research has applied advanced machine learning or explainable artificial intelligence methods to understand the complex nonlinear relationships among occupational stress, self-regulation, technological confidence, and psychological well-being in special education teachers. Third, although prior research has acknowledged the importance of teacher well-being and occupational resilience, few studies have specifically focused on AI integration contexts, where technological transformation adds an additional layer of psychological complexity (Brunsting et al., 2025; Dodur, 2025; Sallin, 2021). Furthermore, the application of explainable AI in educational psychology remains underdeveloped, particularly in identifying interpretable feature contributions to teacher well-being outcomes in real-world educational environments.

Given these limitations, there is a critical need for integrative modeling approaches that combine psychological, occupational, and technological variables within an interpretable artificial intelligence framework. Such approaches can provide not only predictive accuracy but also actionable insights into the relative importance and interaction of key determinants of teacher well-being. Understanding these relationships is essential for designing targeted interventions, improving professional development programs, and supporting sustainable integration of artificial intelligence in special education systems.

The aim of this study was to develop and validate an explainable artificial intelligence model for predicting special education teachers' psychological well-being during artificial intelligence integration by examining the roles of occupational stress, self-regulation, and technological confidence.

2. Methods and Materials

2.1. Study Design and Participants

The present study was conducted using a quantitative, cross-sectional, predictive-correlational design with an explainable artificial intelligence modeling approach. The study aimed to model the psychological well-being of special education teachers during the process of artificial intelligence integration and to determine the predictive roles of occupational stress, self-regulation, and technological confidence. The statistical population consisted of all special education teachers working in public and non-public exceptional schools in Tehran during the 2025–2026 academic year. The final sample included 318 special education teachers from Tehran who were selected through multistage cluster sampling. First, several educational districts of Tehran were selected to ensure geographical diversity across the city, and then special education schools within those districts were identified. In the next stage, eligible teachers were invited to participate in the study. Inclusion criteria consisted of being employed as a special education teacher, having at least one year of teaching experience with students with special needs, having recent exposure to digital or artificial intelligence-based educational tools, and providing informed consent to participate in the study. Teachers who submitted incomplete questionnaires, reported no experience with educational technologies or AI-supported tools, or withdrew from participation were excluded from the final analysis. Participation was voluntary, and all respondents were assured that their information would remain confidential and would be analyzed only in aggregate form. The sample included teachers working with students with intellectual disabilities, autism spectrum disorder, hearing impairment, visual impairment, physical-motor disabilities, learning disabilities, and multiple disabilities, thereby allowing the study to capture a broad range of professional experiences within special education settings.

2.2. Instruments

Data were collected using a demographic and professional information form, the Ryff Psychological Well-Being Scale, the Teacher Stress Inventory, the Short Self-Regulation Questionnaire, and the Computer Self-Efficacy Scale adapted to the context of educational technology and artificial intelligence integration. The demographic and professional information form was designed by the researchers to obtain background information including age, gender, level of education, teaching experience, type of school, type of disability group taught, weekly teaching hours, previous training in educational technology, frequency of using artificial intelligence-based tools, and perceived level of exposure to AI-supported educational applications. This form was used to describe the sample and to control for relevant contextual variables in the statistical and machine-learning analyses.

Psychological well-being was measured using the Ryff Psychological Well-Being Scale. This instrument evaluates psychological well-being as a multidimensional construct and includes the dimensions of autonomy, environmental mastery, personal growth, positive relations with others, purpose in life, and self-acceptance. In the present study, the 42-item version of the scale was used because it provides an appropriate balance between conceptual coverage and practical applicability in educational research. Items are rated on a Likert-type scale ranging from strong disagreement to strong agreement, with some items scored reversely according to the scoring instructions of the scale. Higher scores indicate higher levels of psychological well-being. In the context of the present study, the scale was used as the main outcome variable, reflecting the extent to which special education teachers experienced positive functioning, meaning, self-acceptance, adaptive relationships, and perceived control over their professional and personal environment during the integration of artificial intelligence into educational practice. Previous studies have confirmed the validity and reliability of this scale in teacher, student, and adult populations, and its multidimensional structure has been widely supported in psychological and educational research.

Occupational stress was assessed using the Teacher Stress Inventory developed by Fimian. This scale is specifically designed to measure stress among teachers and is suitable for examining professional strain in educational environments. The instrument includes items related to sources and manifestations of teacher stress, including time

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management, work-related stressors, professional distress, student discipline and motivation, professional investment, emotional manifestations, fatigue manifestations, cardiovascular manifestations, gastrointestinal manifestations, and behavioral manifestations. Responses are rated on a Likert-type scale, and higher scores indicate greater occupational stress. In this study, occupational stress was conceptualized as a central risk factor that may reduce psychological well-being among special education teachers, particularly in the context of increased technological demands and the introduction of artificial intelligence-based tools into instructional, assessment, and administrative practices. The Teacher Stress Inventory has been widely used in educational studies, and previous research has supported its psychometric adequacy, including acceptable internal consistency, construct validity, and applicability across different teaching populations.

Self-regulation was measured using the Short Self-Regulation Questionnaire developed by Carey, Neal, and Collins. This instrument assesses individuals' capacity to regulate thoughts, emotions, behaviors, and goal-directed actions. The scale includes items related to goal setting, planning, monitoring, persistence, decision-making, evaluation of outcomes, and adjustment of behavior in response to feedback. Respondents rate each item on a Likert-type scale, and higher total scores indicate stronger self-regulatory capacity. In the present study, self-regulation was considered a protective psychological resource that may help special education teachers manage occupational pressures, adapt to technological change, and maintain psychological well-being during AI integration. Teachers with higher self-regulation are expected to be more capable of organizing their professional responsibilities, managing emotional reactions to change, learning new technological skills, and sustaining adaptive functioning despite the challenges of working in special education settings. The Short Self-Regulation Questionnaire has been used in a variety of psychological and educational studies, and previous research has reported acceptable reliability and validity for assessing general self-regulatory ability.

Technological confidence was assessed using the Computer Self-Efficacy Scale originally developed by Murphy, Coover, and Owen, with wording adapted to reflect the use of educational technologies and artificial intelligence-supported tools in teaching. This instrument measures teachers' confidence in performing technology-related tasks, learning new digital systems, solving basic technological problems, and using computer-based applications for professional purposes. In the present study, items were framed in relation to educational technology use, AI-assisted instructional planning, digital assessment support, adaptive learning tools, and technology-mediated communication where appropriate. Responses are rated on a Likert-type scale, with higher scores indicating greater confidence in using technology. Technological confidence was included as a key predictor because the successful integration of artificial intelligence in special education depends not only on access to tools but also on teachers' perceived ability to use these tools effectively and responsibly. Higher technological confidence may reduce anxiety toward AI-supported practices, increase willingness to experiment with new tools, and indirectly support teachers' psychological well-being by strengthening perceived competence and professional control. The Computer Self-Efficacy Scale and its adapted forms have shown acceptable psychometric properties in previous studies examining technology use, digital learning, and teachers' confidence in computer-based environments.

2.3. Data analysis

Data analysis was conducted in several stages using both conventional statistical procedures and explainable artificial intelligence techniques. First, the collected data were screened for missing values, outliers, response patterns, and distributional assumptions. Questionnaires with substantial missing data were excluded, and remaining missing values were examined to determine whether they were random. Descriptive statistics, including mean, standard deviation, minimum, maximum, skewness, and kurtosis, were calculated for psychological well-being, occupational stress, self-regulation, technological confidence, and demographic variables. The internal consistency of the research instruments was evaluated using Cronbach's alpha coefficients. Pearson correlation coefficients were then used to examine the bivariate relationships among the main study variables. Before conducting predictive modeling, multicollinearity among predictors was assessed using tolerance and variance inflation factor indices, and the suitability of the variables for regression and machine-learning analysis was evaluated.

In the inferential stage, multiple linear regression analysis was first performed to examine the extent to which occupational stress, self-regulation, and technological confidence predicted psychological well-being among special education teachers. Psychological well-being was

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entered as the criterion variable, and occupational stress, self-regulation, and technological confidence were entered as predictor variables. Relevant demographic and professional variables, including teaching experience, educational level, and frequency of AI tool use, were considered as control variables where appropriate. This stage provided a baseline explanatory model and allowed the direction, magnitude, and statistical significance of linear associations to be examined. The assumptions of regression analysis, including normality of residuals, independence of errors, homoscedasticity, and absence of problematic multicollinearity, were evaluated before interpretation of the model.

In the machine-learning stage, psychological well-being was modeled using supervised predictive algorithms. The dataset was divided into training and testing subsets, with 80% of the data used for model training and 20% used for model testing. To improve model stability and reduce the risk of overfitting, k-fold cross-validation was applied within the training set. Several algorithms were compared, including linear regression, random forest regression, gradient boosting regression, support vector regression, and extreme gradient boosting. Model performance was evaluated using the coefficient of determination, mean absolute error, root mean squared error, and cross-validated prediction error. The best-performing model was selected based on predictive accuracy, generalizability to the test data, and interpretability. Hyperparameter tuning was performed to optimize model performance, particularly for tree-based algorithms such as random forest and gradient boosting.

To explain the predictions of the selected artificial intelligence model, explainable AI procedures were applied. SHAP analysis was used to determine the relative contribution of occupational stress, self-regulation, technological confidence, and relevant background variables to the prediction of psychological well-being. SHAP summary plots, feature importance values, dependence patterns, and individual-level explanations were examined to identify which variables had the strongest positive or negative influence on predicted psychological well-being. This approach allowed the study to move beyond predictive accuracy and provide interpretable evidence regarding how occupational stress, self-regulation, and technological confidence contributed to teachers' well-being during AI integration. In addition, partial dependence patterns were examined to identify whether the relationships between predictors and psychological well-being were linear or nonlinear. The results of the statistical and explainable AI analyses were interpreted together to provide a comprehensive understanding of the psychological and technological factors associated with special education teachers' well-being in the context of artificial intelligence integration.

3. Findings and Results

The study sample consisted of 318 special education teachers working in public and non-public exceptional schools in Tehran. The participants' mean age was 38.74 years with a standard deviation of 7.86, and their ages ranged from 25 to 59 years. In terms of gender distribution, 226 participants were female, representing 71.1% of the sample, and 92 participants were male, representing 28.9% of the sample. Regarding educational level, 102 teachers held a bachelor's degree, 190 held a master's degree, and 26 held a doctoral degree, corresponding to 32.1%, 59.7%, and 8.2% of the total sample, respectively. The mean teaching experience of the participants was 11.42 years with a standard deviation of 6.91, ranging from 1 to 30 years. Based on teaching experience, 65 teachers had five years or less of experience, 94 had between 6 and 10 years of experience, 83 had between 11 and 15 years of experience, and 76 had more than 15 years of teaching experience. Most participants were employed in public special education schools, with 247 teachers working in public schools and 71 teachers working in non-public special education schools. In relation to the main disability group taught, 89 teachers worked primarily with students with intellectual disabilities, 61 with students with autism spectrum disorder, 52 with students with learning disabilities, 35 with students with hearing impairment, 28 with students with visual impairment, 30 with students with physical-motor disabilities, and 23 with students with multiple disabilities. With respect to artificial intelligence and digital educational tool exposure, 121 teachers reported having participated in at least one training course related to educational technology or AI-supported instruction, while 197 teachers reported no formal AI-related training. In terms of frequency of AI-supported tool use, 84 teachers reported low use, 169 reported moderate use, and 65 reported high use. These results indicate that the sample included teachers with diverse educational backgrounds, professional experience, disability-group specialization, and levels of exposure to artificial intelligence-based educational practices.

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Table 1

Descriptive statistics, reliability coefficients, and correlations among the main study variables

Variable	Mean	SD	Min	Max	Skewness	Kurtosis	Cronbach's alpha	1	2	3	4
1. Psychological well-being	176.28	23.64	105	230	-0.29	-0.11	0.92	1			
2. Occupational stress	143.72	27.81	72	213	0.18	-0.37	0.90	-0.56**	1		
3. Self-regulation	107.43	18.52	56	148	-0.13	-0.42	0.88	0.61**	-0.44**	1	
4. Technological confidence	101.86	21.39	43	154	-0.21	-0.28	0.91	0.49**	-0.39**	0.46**	1

**$p < 0.01$.

As shown in Table 1, the descriptive statistics indicated that psychological well-being had a mean score of 176.28 and a standard deviation of 23.64, suggesting a moderate to relatively favorable level of psychological well-being among special education teachers during artificial intelligence integration. Occupational stress had a mean score of 143.72 and a standard deviation of 27.81, indicating that teachers experienced a noticeable level of professional stress in their work environment. The mean score for self-regulation was 107.43, with a standard deviation of 18.52, showing that participants generally reported moderate to high self-regulatory capacity. Technological confidence had a mean score of 101.86 and a standard deviation of 21.39, suggesting that teachers differed considerably in their confidence in using digital and AI-supported educational tools. The skewness and kurtosis values for all main variables were within acceptable ranges, indicating that the distributions did not show serious deviation from normality. The reliability coefficients were satisfactory for all scales, ranging from 0.88 to 0.92, confirming the internal consistency of the instruments used in the study. The correlation matrix revealed that psychological well-being was negatively and significantly associated with occupational stress, meaning that teachers who reported higher levels of occupational stress tended to report lower levels of psychological well-being. Psychological well-being was positively and significantly associated with self-regulation and technological confidence, indicating that teachers with stronger self-regulatory abilities and higher confidence in using technology reported better psychological well-being. Occupational stress was also negatively related to both self-regulation and technological confidence, while self-regulation and technological confidence were positively associated with each other. These findings provide preliminary support for the assumed relationships among the study variables and justify further regression and explainable artificial intelligence modeling.

Table 2

Multiple regression model predicting psychological well-being from occupational stress, self-regulation, technological confidence, and professional background variables

Predictor	B	SE	β	t	p	95% CI for B	VIF
Constant	121.64	8.92	—	13.64	<0.001	[104.09, 139.19]	—
Occupational stress	-0.31	0.03	-0.37	-9.15	<0.001	[-0.38, -0.24]	1.33
Self-regulation	0.53	0.06	0.41	9.45	<0.001	[0.42, 0.64]	1.50
Technological confidence	0.25	0.05	0.22	5.35	<0.001	[0.16, 0.34]	1.41
Frequency of AI-supported tool use	2.84	1.05	0.09	2.70	0.007	[0.77, 4.91]	1.18
Teaching experience	0.14	0.10	0.04	1.35	0.178	[-0.06, 0.34]	1.15
Educational level	1.31	1.13	0.04	1.16	0.248	[-0.91, 3.53]	1.11

Dependent variable: psychological well-being. Model summary: $R = 0.766$, $R^2 = 0.587$, adjusted $R^2 = 0.579$, $F(6, 311) = 73.71$, $p < 0.001$.

Table 2 presents the results of the multiple regression analysis conducted to examine the predictive roles of occupational stress, self-regulation, technological confidence, and selected professional background variables in psychological well-being. The overall regression model was statistically significant, $F(6, 311) = 73.71$, $p < 0.001$, and explained 58.7% of the variance in psychological well-being. This level of explained variance indicates that the combined set of psychological, technological, and professional variables provided a strong explanation of special education teachers' psychological well-being during artificial intelligence integration. Occupational stress was a significant negative predictor of psychological well-being, $\beta = -0.37$, $p < 0.001$, showing that higher levels of stress were associated with lower levels of well-being after controlling for the other variables in the model. Self-regulation was the strongest positive predictor, $\beta = 0.41$, $p < 0.001$, indicating that teachers with greater capacity for planning, emotional control, behavioral monitoring, and adaptive goal management reported substantially higher psychological well-being. Technological confidence was also a significant positive predictor, $\beta = 0.22$, $p < 0.001$, suggesting that confidence in using educational technologies and AI-supported tools contributed meaningfully to teachers' well-being. Frequency of AI-supported tool use was a smaller but statistically significant positive predictor, $\beta = 0.09$, $p = 0.007$, indicating that more frequent use of AI-supported educational tools was associated with slightly higher psychological well-being. However, teaching experience and educational level were not statistically significant predictors when the main psychological and technological variables were included in the model. The variance inflation factor values ranged from 1.11 to 1.50, showing that multicollinearity was not a concern. Overall, the regression results indicate that psychological well-being among special education teachers is shaped primarily by reduced occupational stress, stronger self-regulation, and greater technological confidence rather than by years of experience or educational attainment alone.

Table 3

Comparison of machine-learning models for predicting psychological well-being

Model	Training R^2	Test R^2	MAE	RMSE	Cross-validated RMSE
Multiple linear regression	0.59	0.56	12.48	15.78	16.42
Support vector regression	0.64	0.60	11.64	14.92	15.66
Random forest regression	0.78	0.67	10.31	13.33	13.94
Gradient boosting regression	0.81	0.70	9.76	12.51	13.15
Extreme gradient boosting regression	0.84	0.73	9.21	11.82	12.64

Table 3 shows the comparative performance of the machine-learning models used to predict psychological well-being. The results indicated that all machine-learning models performed at an acceptable level, but their predictive accuracy differed. Multiple linear regression produced a test R^2 of 0.56, indicating that the linear model explained 56% of the variance in psychological well-being in the test data. Support vector regression improved the prediction slightly, with a test R^2 of 0.60 and lower error indices than the linear model. Random forest regression showed stronger performance, with a test R^2 of 0.67, suggesting that nonlinear and interaction-based patterns among occupational stress, self-regulation, technological confidence, and professional background variables contributed to the prediction of teachers' psychological well-being. Gradient boosting regression further improved predictive accuracy, producing a test R^2 of 0.70 and a root mean squared error of 12.51. Among all models, extreme gradient boosting regression demonstrated the best performance, with the highest test R^2 of 0.73, the lowest mean absolute error of 9.21, the lowest root mean squared error of 11.82, and the lowest cross-validated root mean squared error of 12.64. This indicates that the extreme gradient boosting model provided the most accurate and generalizable prediction of psychological well-being. The difference between training and test performance was not excessive, suggesting that the selected model achieved a reasonable balance between model fit and generalizability. Therefore, the extreme gradient boosting model was selected as the final predictive model for the explainable artificial intelligence analysis.

Table 4

Explainable AI feature importance based on SHAP values in the final model

Rank	Predictor	Mean absolute SHAP value	Relative contribution (%)	Direction of influence	Interpretation
1	Occupational stress	10.94	28.1	Negative	Higher occupational stress reduced predicted psychological well-being.
2	Self-regulation	9.87	25.4	Positive	Higher self-regulation increased predicted psychological well-being.
3	Technological confidence	7.26	18.7	Positive	Higher confidence in using technology and AI-supported tools increased predicted psychological well-being.
4	Frequency of AI-supported tool use	3.14	8.1	Positive	More frequent AI-supported tool use was associated with higher predicted well-being, particularly when technological confidence was also high.
5	Teaching experience	2.41	6.2	Nonlinear	Moderate levels of experience showed stronger positive contribution than very low or very high levels.
6	Prior AI-related training	2.08	5.4	Positive	Teachers with prior AI or educational technology training had higher predicted psychological well-being.
7	Educational level	1.35	3.5	Weak positive	Higher educational level had a small positive contribution to predicted well-being.
8	School type	0.91	2.3	Weak	The contribution of public or non-public school type was limited.
9	Age	0.78	2.0	Weak nonlinear	Age had a small and inconsistent contribution to predicted well-being.

Table 4 presents the SHAP-based explainable artificial intelligence results for the final extreme gradient boosting model. The results showed that occupational stress had the highest relative contribution to the prediction of psychological well-being, accounting for 28.1% of the model's explainable predictive structure. The direction of this influence was negative, meaning that higher levels of stress consistently pushed model predictions toward lower psychological well-being scores. Self-regulation was the second most important predictor, accounting for 25.4% of the model's explanatory contribution. Its influence was positive, showing that teachers with stronger self-regulatory capacity were predicted to have higher psychological well-being. Technological confidence ranked third, with a relative contribution of 18.7%, indicating that confidence in using educational technologies and AI-supported tools played a central role in teachers' adaptation to AI integration. Frequency of AI-supported tool use also contributed positively to the model, although its effect was smaller than the effects of the main psychological variables. This finding suggests that using AI-supported tools may be beneficial for well-being when teachers possess sufficient confidence and self-regulatory ability to use these tools effectively. Teaching experience showed a nonlinear contribution, suggesting that experience did not influence well-being in a strictly linear manner. Teachers with moderate levels of experience appeared to benefit more from professional familiarity and adaptability, while very low experience may be associated with uncertainty and very high experience may be associated with stronger resistance to technological change. Prior AI-related training had a positive contribution, indicating that formal exposure to AI and educational technology may support teachers' sense of competence and reduce uncertainty during AI integration. Educational level, school type, and age showed weaker contributions, suggesting that psychological and technology-related factors were more important than demographic and institutional variables in explaining well-being. Overall, the explainable AI results confirmed that occupational stress, self-regulation, and technological confidence were the most influential variables in predicting psychological well-being among special education teachers.

Figure 1

SHAP summary plot of the final extreme gradient boosting model predicting psychological well-being among special education teachers

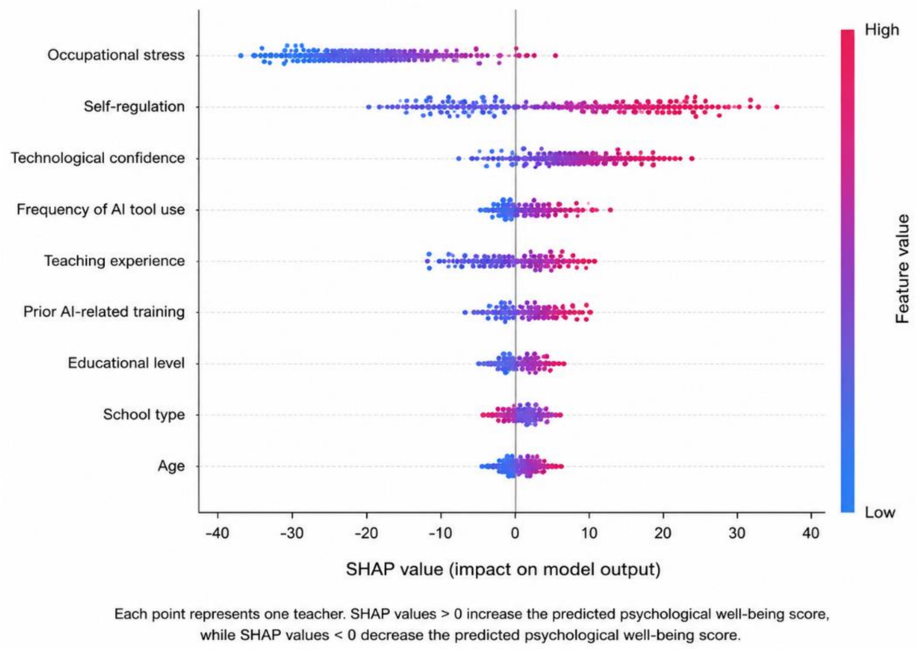

Figure 1 illustrates the overall distribution of SHAP values for the predictors included in the final explainable artificial intelligence model. The figure shows that high occupational stress values were concentrated on the negative side of the SHAP value axis, indicating that occupational stress consistently decreased the predicted psychological well-being score. In contrast, high values of self-regulation and technological confidence were concentrated on the positive side of the axis, indicating that these variables increased predicted well-being. The figure also shows that frequency of AI-supported tool use had a generally positive but more limited effect, suggesting that the mere use of artificial intelligence-based educational tools was not sufficient by itself; rather, its contribution was stronger when accompanied by higher technological confidence and better self-regulation. The dispersion of SHAP values for occupational stress, self-regulation, and technological confidence was wider than the dispersion observed for age, school type, and educational level, confirming that the main psychological and technological variables had greater predictive influence. The overall pattern displayed in the figure supports the interpretation that psychological well-being during artificial intelligence integration is not determined only by access to technology or years of teaching experience. Instead, well-being is most strongly shaped by the interaction between professional stress, personal regulatory resources, and confidence in using technology in special education classrooms.

4. Discussion

The present study aimed to develop an explainable artificial intelligence model for predicting psychological well-being among special education teachers during artificial intelligence integration by examining the roles of occupational stress, self-regulation, and technological confidence. The findings showed that psychological well-being was significantly and negatively correlated with occupational stress and significantly and positively correlated with self-regulation and technological confidence. The regression model explained a substantial proportion of the variance in psychological well-being, indicating that the selected psychological and technological variables had strong explanatory power. Among the predictors, self-regulation emerged as the strongest positive predictor, followed by occupational stress as a strong negative predictor and technological confidence as a significant positive predictor. Frequency of AI-supported tool use also had a smaller but significant positive effect, whereas teaching experience and educational level were not significant predictors after the main psychological and technological variables were entered into the model. In the machine-learning phase, the extreme gradient boosting model produced the strongest predictive performance compared with multiple linear regression, support vector regression, random forest regression, and gradient boosting regression. The SHAP analysis further clarified the structure of the final model by showing that occupational stress, self-regulation, and technological confidence were the most influential features in predicting teachers' psychological well-being.

The negative association between occupational stress and psychological well-being is consistent with the wider body of research indicating that special education teachers are exposed to persistent emotional, instructional, and organizational demands that can undermine occupational well-being. The finding that occupational stress reduced predicted psychological well-being aligns with recent synthesis evidence showing that burnout and occupational strain are central threats to the professional sustainability of special education teachers (Brunsting et al., 2025). Special education teachers often work in environments characterized by intensive individualized instruction, behavioral management demands, documentation requirements, family communication, and collaboration with multidisciplinary teams. These pressures may become more pronounced during technological transitions because teachers must simultaneously meet students' complex needs and learn new digital or AI-based systems. Previous studies have similarly reported that instructional readiness and stress levels among special education teachers were deeply affected by blended and post-pandemic learning conditions, suggesting that technological transitions can increase psychological burden when adequate support is unavailable (Camp et al., 2024; Esternon et al., 2023; Mwamakula, 2024).

This result can also be interpreted in light of qualitative findings on the lived experiences of special education teachers. Studies have documented that teachers working with students with disabilities frequently experience emotional exhaustion, role overload, and feelings of professional invisibility, especially when they lack institutional support and resources (Lariba, 2023; Luisa & Tuvida, 2023). The stress experienced by teachers is not merely a response to classroom events but is shaped by broader social, familial, and institutional expectations. For example, research on special education teachers in the sandwich generation has shown that the coexistence of family caregiving responsibilities and professional demands can intensify psychological strain (Cuadra, 2023). The present findings extend these insights by showing that, in the context of AI integration, occupational stress is not only related to lower well-being at the correlational level but is also the most influential negative feature in an explainable predictive model. This suggests that if AI integration is introduced without reducing workload, strengthening support systems, or improving teachers' sense of control, it may intensify rather than alleviate occupational pressure.

The positive predictive role of self-regulation was one of the most important findings of the study. Self-regulation had the strongest standardized regression coefficient and was the second most important feature in the SHAP analysis. This indicates that special education teachers who are more capable of planning, monitoring their behavior, regulating emotional responses, and adapting to changing instructional conditions are more likely to maintain psychological well-being during AI integration. This finding is consistent with research emphasizing the importance of professional readiness, adaptive practice, and teacher self-management in inclusive and special education environments (Gonzaga, 2024; Moon, 2023; Tundaan, 2023). Self-regulated teachers may be better able to interpret AI tools as manageable professional resources rather than threatening external demands. They may also be more capable of organizing their time, seeking help, experimenting with new instructional methods, and recovering from technological or classroom-related setbacks.

The protective role of self-regulation is also supported by studies highlighting the value of professional development, collaborative learning, and evidence-based practice implementation. Research on training mechanisms for evidence-based practices among educators working with autistic students has shown that structured professional learning can enhance implementation readiness and teacher confidence (Hugh et al., 2023). Similarly, studies on learning action cell practices and lesson study have emphasized that collaborative professional learning improves teachers' competencies and supports reflective practice (Basister et al., 2025; Cruz & Baguio, 2024). From this perspective, self-regulation should not be viewed only as an individual trait but also as a capacity that can be strengthened through professional learning environments. When teachers receive structured opportunities to reflect, collaborate, and practice new methods, they are more likely to develop the self-regulatory skills needed to manage innovation-related uncertainty.

The finding that technological confidence positively predicted psychological well-being is particularly important because the study focused on AI integration. Teachers with higher technological confidence reported higher well-being and received higher predicted well-being scores in the

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explainable AI model. This finding aligns with research showing that teacher attitudes toward artificial intelligence are shaped by AI literacy and AI-related anxiety (Dodur, 2025). When teachers feel competent in using digital systems, they are less likely to experience AI as a source of threat, replacement anxiety, or professional inadequacy. Instead, they may perceive AI-supported tools as resources for instructional planning, assessment, personalization, and classroom support. This interpretation is consistent with research on automated educational systems and students' perceptions of automated writing evaluation, which demonstrates that digital tools can influence educational experiences through perceived usefulness, trust, and confidence in system feedback (Wilson et al., 2024).

Technological confidence may be especially relevant in special education because AI-supported tools can potentially assist with individualized learning, adaptive feedback, communication support, and data-informed decision-making. However, such benefits depend on teachers' ability and willingness to use these tools critically and ethically. Previous research on instructional innovation, specialized tools, and arts-based or adaptive strategies for learners with special needs supports the idea that teacher confidence is central to the successful implementation of new methods (Caballero et al., 2023; Jose Kim et al., 2024; Torregosa, 2024). The present findings add that technological confidence is not only associated with instructional implementation but also with teachers' psychological well-being. In other words, confidence in using AI may reduce uncertainty, increase perceived professional control, and strengthen teachers' sense of competence during educational change.

The smaller but significant role of frequency of AI-supported tool use suggests that actual exposure to AI tools may contribute to psychological well-being, but its effect is weaker than the psychological resources that shape how teachers experience such exposure. This result implies that merely providing AI tools is insufficient. Teachers must also receive training, mentoring, and institutional support. This interpretation is aligned with studies emphasizing capacity development strategies, leadership preparation, and mentoring for special education teachers and leaders (Ciocon, 2023; Omana & Dioneda, 2024; Ortogero et al., 2022). It is also consistent with research on teacher preparation and early-career field experiences, which shows that perceptions of preparation shape professional confidence and later teaching experiences (Goldhaber et al., 2023). AI integration therefore requires more than technical availability; it requires a professional ecosystem that supports gradual learning, guided practice, feedback, and psychological safety.

The non-significant effects of teaching experience and educational level in the regression model are also noteworthy. Although experience and formal education may contribute to professional knowledge, they did not independently predict psychological well-being when occupational stress, self-regulation, and technological confidence were considered. This finding suggests that well-being during AI integration depends less on seniority or degree level and more on adaptive psychological and technological capacities. This interpretation is compatible with evidence showing that teacher readiness in inclusive education is multidimensional and cannot be reduced to years of service alone (Moon, 2023; Tundaan, 2023). Moreover, studies on dual certification, SPED preparation, and inclusive education training show that formal qualifications must be accompanied by applied competence, collaboration, and contextual readiness (Bongabong et al., 2022; Clausen et al., 2022; Howerter et al., 2022). Thus, experienced teachers may still experience stress during AI integration if they lack technological confidence, while less experienced teachers may maintain well-being if they possess strong self-regulation and adequate digital readiness.

The SHAP analysis provided a deeper interpretation of these relationships by identifying the relative importance and direction of each predictor in the final machine-learning model. The fact that extreme gradient boosting outperformed linear and other machine-learning models suggests that the determinants of psychological well-being may involve nonlinearities and interaction effects. This finding supports the methodological value of applying machine learning in special education research, particularly when the goal is to understand complex relationships among professional, psychological, and contextual variables (Sallin, 2021). The explainable AI results made the predictive model more transparent by showing that high occupational stress pushed predictions toward lower well-being, whereas high self-regulation and technological confidence pushed predictions toward higher well-being. Therefore, the study demonstrates that explainable AI can be used not only to improve prediction but also to identify actionable psychological and organizational priorities.

The results also emphasize the relational and ecological nature of teacher well-being. Although the strongest predictors were individual-level variables, teachers operate within institutional, familial, and social networks. Research

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on home–school partnerships, parental involvement, and effective partnerships for children with disabilities shows that teacher well-being and instructional success are shaped by the quality of collaboration among schools, families, and communities (Ang & Spencer, 2022; Custodio et al., 2024; Tenerife et al., 2023). Trust and communication are especially important when introducing new technologies in educational contexts, because families may have concerns about data use, fairness, and the appropriateness of AI-based tools for children with special needs. Broader research on trust among families highlights that social and class differences can shape how educational institutions are perceived, reinforcing the need for transparent, respectful, and culturally responsive communication during innovation processes (Tyson, 2024). In this sense, teachers' technological confidence may also be strengthened when schools cultivate trust-based relationships with families and provide clear explanations of AI use.

The findings further align with strength-based and collaborative perspectives in special education. Strength-based education emphasizes identifying capacities, resources, and positive developmental possibilities rather than focusing exclusively on deficits (Eunice Tan Meng & Mark Kuo Cheng, 2024). The present study reflects this orientation by showing that self-regulation and technological confidence function as protective assets for teachers. Similarly, collaborative models in teacher education and international service-learning have emphasized the importance of professional cooperation, reflective learning, and cross-contextual exchange (Rose et al., 2021; Voytecki & Anderson, 2021). These collaborative practices may be particularly valuable during AI integration because teachers need opportunities to discuss concerns, share successful strategies, and build collective confidence. Therefore, supporting psychological well-being during AI adoption requires a shift from isolated individual responsibility to collaborative institutional development.

5. Conclusion

Overall, the findings indicate that special education teachers' psychological well-being during AI integration is shaped by a dynamic balance between risk and protective factors. Occupational stress operates as a major risk factor that reduces well-being, while self-regulation and technological confidence operate as protective factors that support adaptation. AI-supported tool use can be beneficial, but its positive effect appears to depend on the presence of psychological readiness, training, and institutional support. By combining regression analysis with explainable AI, the study provides both statistical and interpretable evidence that teacher well-being in the era of AI cannot be understood through technological variables alone. Instead, it must be approached as a psychological, occupational, and organizational phenomenon embedded in the realities of special education practice.

6. Limitations & Suggestions

This study had several limitations that should be considered when interpreting the findings. First, the cross-sectional design limits the ability to draw causal conclusions about the relationships among occupational stress, self-regulation, technological confidence, and psychological well-being. Although predictive modeling can identify important patterns, it cannot establish temporal direction. Second, all variables were measured through self-report questionnaires, which may increase the possibility of response bias, social desirability, or common method variance. Third, the sample was limited to special education teachers in Tehran, and therefore the findings may not be fully generalizable to teachers in other cities, rural regions, or different educational systems. Fourth, although the study included indicators of AI tool use and technological confidence, it did not directly observe classroom-level AI implementation or evaluate the quality, type, or ethical design of the AI tools used by teachers.

Future research should use longitudinal designs to examine how psychological well-being changes before, during, and after AI integration in special education settings. Such designs would help clarify whether technological confidence and self-regulation protect teachers from stress over time or whether improved well-being increases teachers' willingness to use AI-supported tools. Future studies should also include mixed-methods approaches by combining quantitative predictive modeling with interviews, observations, and case studies to capture teachers' lived experiences more deeply. In addition, future research should examine moderating and mediating mechanisms, such as institutional support, AI literacy, professional development quality, perceived ethical risk, workload, and school leadership. Comparative studies across different regions, school types, and disability groups would also strengthen the generalizability of findings and provide a more comprehensive understanding of AI integration in special education.

The findings suggest that schools and educational policymakers should approach AI integration as both a technological and psychological process. Professional development programs should not only teach teachers how to use AI-supported tools but also strengthen their self-regulation, stress management, and confidence in technology use. School leaders should reduce unnecessary workload, provide practical training, create peer-support systems, and ensure that teachers have time to experiment with AI tools without fear of failure. AI-related training should be gradual, hands-on, and directly connected to the realities of special education classrooms. In addition, schools should build transparent communication with families and clarify how AI tools are used to support individualized instruction, accessibility, and student progress. Supporting teacher well-being should be treated as a core condition for successful and ethical AI integration in special education.

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Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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Declaration

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