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THE MEDIATING ROLE OF GENERAL ATTITUDE TOWARDS ARTIFICIAL INTELLIGENCE IN THE RELATIONSHIP BETWEEN THRIVING AT WORK AND PSYCHOLOGICAL WELL-BEING

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Abstract

This research examines the mediating role of general attitudes towards artificial intelligence in the effect of employees' levels of thriving at work (a personal resource) on their psychological well-being, within the framework of the Job Demands and Resources (JDR) theory. The limited number of studies in the literature that integrate attitudes towards self-development, work psychology, and artificial intelligence based on the Job Demands and Resources theory constitute the basis for this research. A quantitative research approach was adopted in the study; data obtained from 399 healthcare workers using a convenience sampling method and a two-stage data collection process were analysed using the PROCESS Macro (Model 4). The findings show that employees' levels of thriving at work increase their attitudes towards artificial intelligence and that these attitudes positively influence their psychological well-being. Consequently, this research adds a technology-based perspective to the Job Demands and Resources theory and offers important insights for organisations to develop employee-focused technology integration and human resources strategies.

Keywords: Psychological well-being, Thriving at work, General attitude towards artificial intelligence, Job demands-resources theory.

İŞ YERİNDE KENDİNİ YETİŞTİRME İLE PSİKOLOJİK İYİ OLMA ARASINDAKİ İLİŞKİDE YAPAY ZEKÂYA YÖNELİK GENEL TUTUMUN ARACI ROLÜ

Öz

Bu araştırma, İş Talepleri ve Kaynakları (İTK) kuramı çerçevesinde, çalışanların işte kendini yetiştirme düzeylerinin (kişisel kaynak) psikolojik iyi oluşları üzerindeki etkisinde yapay zekâya yönelik genel tutumların aracılık rolünü incelemektedir. İşte kendini yetiştirme, iş psikolojisi ve yapay zekâya yönelik genel tutumları İş Talepleri ve Kaynakları kuramı temelinde bütünleştiren çalışmaların literatürde sınırlı olması, bu araştırmanın çıkış noktasını oluşturmaktadır. Araştırmada nicel araştırma yaklaşımı benimsenmiş; kolayda örneklem yöntemi ve iki aşamalı veri toplama süreci kullanılarak 399 sağlık çalışanından elde edilen veriler PROCESS Macro (Model 4) aracılığıyla analiz edilmiştir. Bulgular, çalışanların işte kendini yetiştirme düzeylerinin yapay zekâya yönelik tutum düzeylerini artırdığını ve bu tutumlar aracılığıyla psikolojik iyi oluşlarının olumlu yönde etkilendiğini göstermektedir. Sonuç olarak, bu araştırma İş Talepleri ve Kaynakları kuramına teknoloji temelli bir bakış açısı kazandırmakta; kurumlara, çalışan odaklı teknoloji entegrasyonu ve insan kaynakları stratejileri geliştirilmesine yönelik önemli çıkarımlar sunmaktadır.

Anahtar kelimeler: Psikolojik iyi olma, İş yerinde kendini geliştirme, Yapay zekaya yönelik genel tutum, İş talepleri-kaynakları teorisi.

1. INTRODUCTION

In recent years, the importance of researching individuals' psychological well-being and happiness has increased in the aftermath of challenging and traumatic events such as the COVID-19 pandemic and the 6 February Kahramanmaraş earthquake. The uncertainty, heightened anxiety, and significant losses experienced during these periods have adversely affected individuals' psychological well-being. Psychological well-being, however, plays a crucial role in enhancing individuals' quality of life and overall happiness and is also a key factor in productivity and effectiveness in working life (Gültekin & Bayramoğlu, 2021).

In these stressful situations, which also affect work life, employees need access to resources in the workplace to maintain their well-being. In this context, the job demands-resources theory aims to establish a balance between the resources available to employees and the demands they face. It provides a strong theoretical framework for understanding the processes of protecting employees from burnout and increasing their motivation (Demerouti, Bakker, Nachreiner & Schaufeli, 2000). The job demands-resources theory is also important in terms of contributing to the development and innovation processes of employees. In this context, the aim of the study is to determine psychological well-being and the factors affecting psychological well-being based on the theory of job demands and resources. One of the subjects that positively affects psychological well-being is thriving at work. Therefore, the relationship between thriving at work and psychological well-being is examined first. The concept of thriving at work is a matter that supports sustainable success and innovation by enabling employees to experience both energy and learning processes together in the work environment (Spreitzer et al., 2005). Thriving at work is a factor that can reduce negative emotions such as disappointment and increase psychological well-being, i.e., positive psychology. It is a personal resource (Yousaf et al., 2019; Huang & Zhou, 2024). Based on the job demands-resources theory, there are a limited number of studies that address the subjects of thriving at work and mental health or psychological well-being together (Bai et al., 2025). Addressing these three subjects together is important in order to develop recommendations for the long-term success of organisations by protecting the well-being of employees.

The research also addresses the subject of the mediating effect of general attitudes towards artificial intelligence on the relationship between thriving at work and well-being. Grand View Research (2025) estimates that the global market size of artificial intelligence will be 279.22 billion in 2024 and will grow at a CAGR of 35.9% to reach 1,811.75 billion by 2030. According to a study conducted by McKinsey & Company (2025), 78% of participants stated that they used artificial intelligence in at least one of the tasks they performed. The rapid spread of artificial intelligence shows that it is not only a tool that provides technical efficiency, but also a factor that affects the work experience and psychological well-being of employees. The integration of artificial intelligence into work life cannot be considered independently of user experience and psychological well-being. However, there is a gap in the literature regarding the examination of the relationship between artificial intelligence and psychological well-being (Giuntella, König & Stella, 2025). Furthermore, the literature explains the impact of AI on employee well-being not directly, but through indirect mechanisms such as job design, task load management, and decision support systems (Valtonen et al., 2025; García-Madurga et al., 2024). At this point, the concept of thriving at work emerges as a critical personal resource in understanding the effects of AI on employees. Thriving at work means that individuals show simultaneous development in both learning and vitality dimensions in the work environment and is considered a strong determinant in positive psychology and work motivation literature (Merkuž, Zupič, & Mihelič, 2024).

According to the Job Demands–Resources (JD-R) model, personal resources such as thriving at work enable employees to use job resources (e.g., AI technologies) more effectively, reduce the negative effects of job demands, and strengthen motivational processes (Bakker & Demerouti, 2017). In this context, it is thought that employees with high levels of thriving are more likely to adopt and effectively use the job resources offered by AI. Thus, AI mediates the relationship between thriving and well-being. However, a review of the literature reveals that there are very few studies examining the mediating relationship between thriving at work, the adoption of AI technologies, and employee well-being. Most existing studies focus on the technical effectiveness of AI (e.g., increased productivity, reduced error rates), while the effects on employees' psychosocial outcomes and individual resources have been examined only to a limited extent (Brynjolfsson et al., 2025). To fill this gap in the literature, within the framework of job demands–resources theory, does the general attitude of employees towards artificial intelligence play a mediating role in the relationship between Thriving at work (job resources) and psychological well-being? This research question is examined in the study. It is assumed that general attitudes toward artificial intelligence play a mediating role in the relationship between thriving at work and psychological well-being. This is because employees who thrive at work are more open to new experiences and change (Spreitzer et al., 2005), and this openness may make it easier for them to view AI technologies as opportunities, which in turn may ultimately support their psychological well-being.

Finally, there is very little research explaining the mechanism between JDR, thriving at work, artificial intelligence, general attitude, and psychological well-being variables. This mechanism, which will be explained based on the JDR model, fills a gap in the literature and has original value in terms of examining the effect of technology adoption on employee well-being.

2. CONCEPTUAL FRAMEWORK AND HYPOTHESIS

2.1. Job demand research theory (JDR)

Employees' psychological well-being, motivation-based processes, and performance are shaped by the demands of the job and the resources that enable these demands to be met. JD-R addresses job demands and resources within a model framework. Physical workload, time pressure, contact with the person being served, physical working environment, and shift work are subjects that constitute job demands, while feedback, rewards, control over work, participation, job security, and managerial support are factors that constitute job resources (Demerouti, Bakker, Nachreiner & Schaufeli, 2001). Although the origins of the JD-R do not date back very far, it has become the focus of interest for many researchers today and has begun to be widely used. The JD-R emphasises two fundamental processes. The first is the exhaustion process, which states that high job demands lead to energy loss, which in turn leads to exhaustion. The second is the motivation process. It is stated that an abundance of job resources increases motivation, which in turn contributes to high job performance (Bakker & Demerouti, 2017). When designing jobs, it is important to pay attention to the balance between job demands and resources. High job demands must be supported by sufficient resources. Increasing employee satisfaction and reducing psychosocial risks may be important factors in improving employee performance. This model is used for these job design processes (Schaufeli & Taris, 2014).

2.2. Psychological well-being and thriving at work

When the subject of psychological well-being is considered historically, it has been approached from two perspectives: hedonistic and eudaemonic. The hedonistic approach includes components such as happiness, positive affect, negative affect, and life satisfaction. The eudaemonic approach emphasises positive development indicators based on personal development and the development of talents (Tara & Iqbal, 2023). In this sense, psychological well-being refers to positivity based on self-acceptance, positive relationships with others, autonomy, environmental mastery, purpose, life, and personal development (Ryff, 1989). Rather than focusing on negative psychological states in working life, examining and increasing positive psychological states can be an important subject in order to achieve this (Telef, 2013).

In recent years, a relationship has been established between JD-R and psychological well-being. Because the demands can also affect the well-being of employees (Claes et al., 2023). Psychological well-being has been studied in conjunction with various subjects. For example, Sharma and Sharma (2024) examined the mediating role of supportive voice in the relationship between job autonomy and psychological well-being based on the job demands theory. It was found that supportive voice positively affects well-being. Li and co-workers (2025) expanded the JD-R model within the JD-R 3.0 framework and found that after-hours connectivity leads to increased psychological distress, creating a psychological breach, and that the negative effects of this psychological contract breach are mitigated through organisational support. These findings indicate that high job demands negatively affect psychological well-being and that job performance can be maintained when job resources and demands are balanced. Psychological well-being is important for a sustainable work life and a peaceful work environment. A high level of psychological well-being enables employees to cope better with stress and contribute to their own development. In this context, another concept that has recently come to the fore in supporting the enhancement of psychological well-being is thriving at work. According to Peters et al. (2021), thriving at work means that employees reach their full potential not only in terms of their work experience but also at a higher level, such as in their family and community. Here, a definition is made that includes not only the positive mental development of employees but also their physical and social conditions. Thriving at work is conceptualized as a construct comprising two sub-dimensions: Vitality, which reflects individuals' internal energy and aliveness in the workplace, and learning, which represents ongoing self-development and growth at work (Spreitzer et al., 2005; Porath et al., 2012). Thriving at work is a personal resource related to well-being (Stansfeld et al., 2013). A review of the literature reveals a positive relationship between thriving at work and positive work conditions. For example, trust (Koçak, 2019), security and job satisfaction (Okros & Virga, 2023), psychological capital, positive emotions, proactive personality, managerial support, empowerment, and job meaningfulness (Kleine et al., 2019; Liu et al., 2021). Based on the findings of previous studies (Wei, Ding, & Sun, 2025; Huang & Zhou, 2024), a significant and positive relationship has been identified between thriving at work and psychological well-being. In this context, the first hypothesis of the study was developed as follows.

H1: Thriving at work positively and significantly affects psychological well-being.

2.3. Thriving at work and general attitude towards artificial intelligence

In recent years, there has been rapid development in measurement instruments assessing attitudes toward artificial intelligence. Various scales have been developed to examine individuals' thoughts, perceptions, and feelings towards artificial intelligence. This is because the effective and efficient use of artificial intelligence and how this process can be developed based on ethical criteria are among the greatest concerns today. For example, Schepman and Rodway (2020) developed an artificial intelligence general attitude scale based on positive attitudes towards the appeal of artificial intelligence and negative attitudes based on risky perspectives on artificial intelligence. Wang and Wang (2022) developed a scale to measure concerns arising from the development of artificial intelligence. Suh and Ahn (2022) developed a scale based on measuring attitudes toward artificial intelligence in terms of benefits, risks, and usage. While self-moving robots have advanced significantly, the further design and optimisation of these technologies require specific expertise and advanced technical skills. In this context, employees' tendencies to develop their professional knowledge and competencies significantly influence their attitudes toward artificial intelligence technologies and their level of adoption of these technologies (Xiaomei, Sen, & Qin, 2021). According to Leong et al. (2025), thriving at work has a role in boosting innovative work. In these studies, thriving at work has been considered a precursor in AI-based attitude processes. According to the study by Yu, Zhu, and Ren (2025), as AI acceptance increases, so does thriving at work. The lack of AI-based adaptation processes, on the other hand, can lead to resistance and have a negative impact. Here, AI is considered a precursor that influences thriving at work. In other words, when examining the relationship between thriving at work and AI in the literature, it has been observed that they positively influence each other. In this context, the second hypothesis of the study is based on the works of Xiaomei, Sen and Qin (2021) and Leong et al. (2025), in which thriving at work is considered a precursor that will develop a positive attitude towards artificial intelligence and influence its use. Within this scope, the second hypothesis of the study is as follows:

H2: There is a positive and significant relationship between thriving at work (H2a: vitality, H2b: learning) and general attitude towards artificial intelligence.

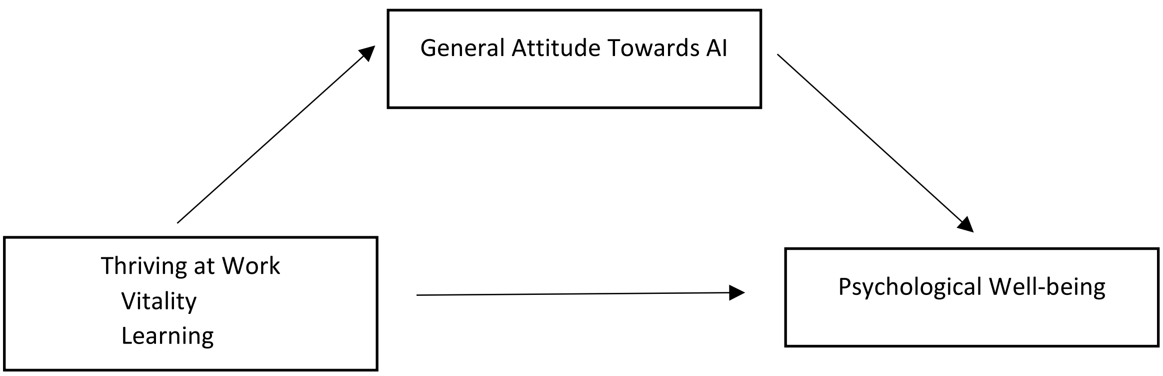
2.4. The mediating role of general attitude towards artificial intelligence

Thriving at work is a positive psychological state that refers to employees' simultaneous development in both learning and vitality dimensions in the work environment (Spreitzer et al., 2005). Thriving supports both the emotional and cognitive dimensions of well-being by strengthening individuals' innovative behaviours and ability to adapt to change in the work environment. According to JDR, thriving at work is also considered a personal resource. This is because both learning and vitality dimensions increase an individual's capacity to cope with work challenges and strengthen motivational processes (Merkuž, 2024). This enables employees to adapt more easily to technological innovations (e.g., artificial intelligence) and benefit from them. Artificial intelligence (AI) technologies can potentially support well-being by automating work processes, accelerating decision-making processes, and reducing employees' cognitive load (García-Madurga et al., 2024; Brynjolfsson et al., 2025). AI technologies can be considered a job resource according to the JD-R model. When applied correctly, AI can reduce employees' cognitive load by providing benefits such as task automation, quick access to information, and decision support mechanisms (Valtonen et al., 2025; García-Madurga et al., 2024). Thus, AI use is expected to strengthen motivational processes and enhance well-being by increasing job resources. Moreover, employees with high levels of thriving are more willing to adopt and effectively use innovative technologies, allowing them to experience the benefits of AI more effectively. Positive psychology literature shows that thriving strengthens individuals' openness to learning, adaptation skills, and positive attitudes toward change (Brynjolfsson et al., 2025). These characteristics are thought to facilitate the integration of advanced technologies such as AI into work processes, enabling employees to derive maximum benefit from technology. Therefore, thriving at work can indirectly increase employees' well-being levels by increasing AI usage. According to the JD-R model, personal resources (thriving) facilitate the effective use of job resources (AI usage). Employees with high levels of thriving utilise the resources offered by AI technologies more effectively, reduce the negative effects of job demands, and increase motivational outcomes. In this context, AI usage can play a mediating role in the effect of thriving on well-being. In this context, the final hypothesis of the study is formulated as follows.

H3: General attitude towards AI mediates the relationship between thriving at work (H3a: Vitality, H3b: Learning) and psychological well-being.

The research model is shown in Figure 1.

Figure 1. *Research Model.*



3. METHOD

The research was designed as a quantitative research method. A two-stage data collection process was applied in the study. In the first time frame, the thriving at work scale and demographic information were used, while in the second time frame, the general attitude towards artificial intelligence and psychological well-being scales were used. Data was collected from a total of 489 participants in the first data collection phase. The second data collection phase was conducted at least two weeks after the first application, and data was collected from 449 participants in this phase. A self-report-based coding method was used to match participants' responses in both data collection phases. Participants were asked to create a code that they could remember but that would not directly reveal their identity. This code consisted of two letters (e.g., the initials of their first and last names) combined with the last two digits of their licence plate number or telephone number (e.g., FG-6138). The same code was to be used in both data collection phases. The data collected in the first and second phases were matched using these codes created by the participants. The data of participants whose codes matched exactly were included in the analysis process, while participants with missing, incorrect or mismatched codes were excluded from the analysis. As a result of the matching process, data from 399 participants who completed both measurement waves were retained for analysis. The reduction in sample size between the two waves was attributable to non-participation in the second measurement and/or incorrect or inconsistent self-generated codes. All analyses were conducted using data from participants who provided valid responses at both time points, resulting in an overall data attrition rate of 20.45% from the initial sample.

In the study, the convenience sampling method was preferred due to time and access constraints and the demanding working conditions of healthcare professionals, as it allowed for quick and practical access to participants (Creswell, 2012). The sample of the study consists of healthcare workers (nurses). The nursing profession requires a high level of knowledge, skills, and the ability to continuously develop oneself (Flinkman, Isopahkala-Bouret & Salanterä, 2013). Moreover, artificial intelligence applications are increasingly being used today, and nurses are supporting this process to improve their work processes (Topaz & Ronquillo, 2023). Therefore, the subjects to be researched are related to nurses. For this reason, it will be important to understand the relationship between the answers given by nurses and the variables.

3.1. Participants and procedure

An application was submitted to the Scientific Research and Publication Ethics Committee of Gümüşhane University prior to initiating this research. The Committee decided that the research was ethically acceptable with its decision dated 25 June 2025, reference number E-95674917-108.99-340329. After obtaining institutional permission, the research process was started. Confidentiality and anonymity were ensured throughout the research process, and the study was conducted in accordance with ethical principles. The data was obtained from 399 nurses. The age of the participants ranged between 21 and 69 (M= 29.64, SD= 0.715). 65.7% (N=262) of the participants were female and 34.3% (N=137) were male. The majority of participants (58.4%) were bachelor's degree graduates (N=233). 74.9% (N=299) of the participants stated that they had no experience with artificial intelligence, while 25.1% (N=100) stated that they had experience with artificial intelligence. Participants had at least 1 year of work experience and up to 25 years of work experience (M=4.43, SD=4.52).

3.2. Measures

Thriving at work: A scale developed by Porath et al. (2012). It consists of a total of 8 items from the sub-dimensions of vitality and learning. It was adapted into Turkish by Koçak (2016). Measurement was performed using a 6-point Likert scale ranging from 1=Strongly Disagree to 6=Strongly Agree.

General Attitude Towards Artificial Intelligence Scale Short Form: The General Attitude Toward Artificial Intelligence Scale, developed by Grassini (2023), was also used in the studies conducted by Türk, Batuk, Kaya, and Yıldırım (2025). The scale and permission to use it were obtained from the original authors. The scale consists of four items and is measured using a 10-point Likert scale ranging from 1 (Strongly Disagree) to 10 (Strongly Agree). The Cronbach’s alpha coefficient of the scale was 0.89, indicating high internal consistency.

Psychological well-being scale: The psychological well-being scale was adapted into Turkish by Telef (2013) with permission from Ed Diener. The scale consists of eight items on a single dimension. The

Cronbach's alpha internal consistency coefficient obtained in the reliability study of the scale was calculated as 0.80.

Information was obtained from participants regarding gender, age, educational status, artificial intelligence experience, and work experience as control variables.

3.3. Results

This part shows the descriptive statistics and correlation analysis results for the research variables. Before the mediation analyses, the means, standard deviations, and Pearson correlation coefficients were calculated to check the strength and direction of the relationships between the variables. This step provides a preliminary assessment of the proposed research model.

Table 1. *Standard error, mean and correlation analysis results.*

Variables	SD	M	1	2	3	4	5	6	7	8	9
1. Gender	1,34	0,47	1	,149**	-,109*	,114*	,054	-,026	-,016	-,037	-,041
2. Age	29,65	7,15		1	,074	-,018	,488**	,001	-,032	-,185**	-,107*
3. Education	3,59	0,68			1	-,060	,006	,077	,042	,004	,002
4.AI Experience	1,75	0,43				1	-,056	,013	,014	-,072	,033
Work 5.Experience	4,43	4,52					1	-,050	-,008	-,060	-,073
6.Vitality	4,04	1,58						1	,784**	,279**	,589**
7.Learning	4,38	1,50							1	,379**	,612**
8.GATAI	6,11	2,83								1	,449**
9.Well-being	3,78	0,99									1

Notes: GATAI: General attitude towards artificial intelligence, AI: Artificial intelligence, *:p<0.05, **:p<0,001, ***:p=0.000, SD: Standard Deviation.

According to the findings in Table 1, positive and significant relationships were found between the variables in general. A moderate-high level ($r = 0.589$, $p < .01$) positive relationship was found between vitality and psychological well-being. The relationships between learning and psychological well-being ($r = 0.612$, $p <0.01$) and AI ($r = 0.379$, $p < 0.01$) were at medium levels, while the relationship between general attitude toward artificial intelligence and psychological well-being was at a medium level ($r = 0.449$, $p < 0.01$). The relationships between demographic variables and psychological variables were generally weak, with low levels of significance.

Following the correlation analysis, the construct validity and reliability of the measurement scales were further assessed through factor analysis. The results indicated a Kaiser–Meyer–Olkin (KMO) value of 0.945, demonstrating that the sample was highly suitable for factor analysis (Hair, Black, Babin, & Anderson, 2022). In addition, Bartlett's test of sphericity was statistically significant ($\chi^2(190) = 11058.94$, $p < 0.001$), confirming the presence of sufficient correlations among the variables to proceed with factor analysis (Field, 2018). Principal component analysis yielded four factors with eigenvalues greater than 1, accounting for 86.58% of the total variance. Examination of the rotated component matrix showed that all items loaded strongly on their respective factors (loadings > 0.73), with no evidence of cross-loading, supporting the adequacy of the factor structure. Table 2 presents the results of the factor analysis, including AVE, CR, and reliability coefficients.

Table 2. *Factor analysis, AVE, CR and Cronbach's Alpha results*

Variables	1	2	3	4	AVE	CR	Cronbach's Alpha
PW1	0,782				0,64	0,93	0,95
PW2	0,805						
PW3	0,828						
PW4	0,763						
PW5	0,835						
PW6	0,822						
PW7	0,767						
PW8	0,781						
V1		0,848			0,72	0,91	0,97
V2		0,851					
V3		0,856					
V4		0,835					
GATAI1			0,935		0,58	0,97	0,982
GATAI 2			0,948				
GATAI 3			0,936				
GATAI 4			0,937				
L1				0,736	0,72	0,95	0,97
L2				0,790			
L3				0,791			
L4				0,801			

Notes: PW: Psychological well-being, V: Vitality, GATAI: General attitude towards artificial intelligence, L: Learning, AVE: Average Variance Extracted, CR: Composite Reliability, The numbers indicate the question item number sequence.

Following the confirmatory factor analysis, convergent validity and reliability were assessed for each construct. The average variance extracted (AVE) values ranged from 0.58 to 0.72, exceeding the recommended threshold of 0.50 (Fornell & Larcker, 1981) and thereby supporting convergent validity. In addition, the composite reliability (CR) values ranged from 0.91 to 0.97, surpassing the minimum criterion of 0.70 suggested by Hair, Black, Babin, and Anderson (2022), which indicates a high level of measurement reliability. Cronbach's alpha coefficients ranged from 0.95 to 0.982. In the literature, alpha values above 0.70 are considered acceptable, while those above 0.90 are considered excellent (Nunnally & Bernstein, 1994). The high alpha values in this study stem from the items measuring a conceptually narrow and homogeneous structure, reflecting the high consistency among the statements in the scale. In this context, high alpha values indicate that the scale items consistently reflect the targeted structure and that the unidimensional structure is represented in a stable manner (Tavakol & Dennick, 2011; Streiner, 2003).

To examine the adequacy of the proposed measurement model, confirmatory factor analysis (CFA) was conducted following the exploratory factor analysis. The results indicated that when all variables were loaded onto a single-factor model, the fit indices were poor ($\chi^2/df = 34.63$, GFI = 0.313, CFI = 0.484, TLI = 0.423, NFI = 0.478, RMSEA = 0.291, and Standardised RMR = 0.178), which is an expected outcome and suggests the presence of multiple underlying constructs. In contrast, the four-factor model demonstrated substantially improved fit indices ($\chi^2/df = 3.60$, GFI = 0.860, AGFI = 0.820, CFI = 0.962, TLI = 0.955, NFI = 0.948, RMSEA = 0.081, and Standardised RMR = 0.0338). According to the criteria proposed by Hu and Bentler (1999) and Kline (2016), the CFI, TLI, and NFI values indicate excellent model fit, while the GFI and AGFI values suggest acceptable fit. In addition, the RMSEA value falls within the acceptable range, and the Standardised RMR value below 0.05 further supports the model's good fit in terms of residuals.

3.4. Hypothesis testing and findings

3. 4. 1. Simple Linear Regression Analysis Results

The first hypothesis of the study was tested. A simple linear regression analysis was conducted to test the relationship between the dependent variable of psychological well-being and the independent variable of vitality and the learning sub-dimension of thriving at work. According to the regression analysis results, the model was found to be significant ($F(2,396) = 134.88$, $p < .001$), and the independent variables (vitality and learning) explained 40.5% of the variance in the dependent variable of psychological well-being ($R^2 = 0.405$). According to the standardised coefficients, learning ($\beta = 0.389$, $p< 0.001$) was found to have a greater effect on psychological well-being than vitality, while the vitality variable ($\beta = 0.284$, $p < 0.001$) was found to have a lesser effect than the learning dimension. Both variables were found to have a positive and significant effect. H1a and H1b were accepted.

To test hypothesis two, the relationship between thriving at work (vitality and learning) and general attitude towards artificial intelligence was tested. According to the results of the simple linear regression analysis, the model is significant ($F(2,396) = 33.47$, $p < 0.001$), and the coefficient of determination ($R^2 = 0.145$) indicates that approximately 14.5% of the variance in the dependent variable is explained by the independent variables. According to standardised coefficients, there is a positive and significant relationship between the learning variable and general attitude towards artificial intelligence ($\beta = 0.416$, $p< .001$). However, no significant relationship was found between the liveliness variable and general attitude towards artificial intelligence ($\beta = -0.047$, $p = 0.530$). Based on this result, H2a is rejected, while H2b is accepted.

Demographic variables (gender, age, educational status, artificial intelligence experience, and work experience) were included in the research model as control variables and examined through regression analyses. The results indicated that these variables did not have a statistically significant effect on the dependent variables, nor did their inclusion lead to a meaningful increase in the explained variance (R^2). Accordingly, in line with methodological recommendations, only statistically significant and theoretically justified variables were retained, and demographic variables were excluded from the final analysis models to maintain model simplicity.

3. 4. 2. Mediation effect analysis

According to the mediation effect analysis results, artificial intelligence has a significant total effect on psychological well-being (Y) through the mediator variable (W) of vitality (X) ($B = 0.37$, $t = 14.51$, $p<0.001$). The 95% confidence interval is [0.32, 0.42] and does not include zero. This finding indicates that X has a positive and significant effect on Y (Preacher & Hayes, 2008; Gürbüz, 2025). When examining the direct effect, the effect of the independent variable (X) on the dependent variable (Y) was found to be $B = 0.32$, $t = 12.77$, $p< 0.001$, with a 95% confidence interval of [0.26, 0.36]. This result indicates that the effect of the independent variable on the dependent variable remains statistically significant even after controlling for the mediating variable (Hayes, 2022). The indirect effect (through the mediating variable m) was found to be $B = 0.05$, with a 95% confidence interval of [0.03, 0.09]. The fact that the confidence interval does not include zero indicates that the effect of the mediator variable is statistically significant. H3a is accepted.

Tablo 3. *PROCESS macro (model 4) analysis result of the mediating role of GATAI between vitality and psychological well-being.*

Independent Variable		Outcome Variables (Psychological Well-Being)			
		b	S.E.	b	S.E.
Constant		4,09***	0,38	1,85	0,12
Vitality (X)		0,50***	0,09	0,32	0,02
GATAI (M)				0,11	0,01
F		33,52		152,14	
R^2		0,08		0,43	
Effect Type	B (β)	Std. Error	t	95% CI [Lower, Upper]	
Total Effect	0,37	0,03	14,51	[0,32 – 0,42]	
Direct Effect	0,32	0,02	12,77	[0,26 – 0,36]	
Indirect Effect	0,05	0,05		[0,03 – 0,09]	

Notes: GATAI: General attitude towards artificial intelligence; p < .05,* p < .01, ** p < .001,*** , b = Standard coefficient; S.E.: Standart Error.

The analysis results indicate that GATAI (M) had a significant mediating role in the total effect of the learning sub-dimension of thriving at work (X) on psychological well-being (Y) (B = 0.41, t = 15.41, p <0.001). The 95% confidence interval [0.36, 0.46] does not include the zero value. This finding indicates that learning has a significant and positive effect on psychological well-being (Preacher & Hayes, 2008; Gürbüz, 2025). When examining the direct effect, the effect of learning on psychological well-being was found to be B = 0.34, t = 12.57, p < 0.001, with a 95% confidence interval of [0.29, 0.40]. This indicates that the effect of the independent variable on the dependent variable continues to be significant when the mediator variable is included (Hayes, 2022). The indirect effect (through the mediator variable of general attitude toward artificial intelligence) was found to be B = 0.06, with a 95% confidence interval of [0.03, 0.09]. The fact that the confidence interval does not include zero indicates that the effect of the mediator variable is statistically significant. This result reveals that the effect of X on Y occurs both directly and indirectly through the mediator variable, thus confirming that the model has a mediational structure (Baron & Kenny, 1986).

Tablo 4. *PROCESS macro (model 4) analysis result of the mediating role of GATAI between learning and psychological well-being.*

Independent Variable		Outcome Variable (Psychological Well-Being)			
		b	S.H.	b	S.H.
Constant		2,96	0,40	1,74	0,12
Learning (X)		0,72	0,09	0,34	0,03
GATAI (M)				0,09	0,01
F		66,65		146,84	
R^2		0,14		0,43	
Effect Type	B (β)	Std. Error	t	95% CI [Lower, Upper]	
Total Effect	0,41	0,02	15,41	[0,36 – 0,46]	
Direct Effect	0,34	0,03	12,57	[0,29 – 0,40]	
Indirect Effect	0,06	0,02		[0,03 – 0,09]	

Notes: GATAI: General attitude towards artificial intelligence; p < .05,* p < .01, ** p < .001,*** , b = Standard coefficient; S.E.: Standart Error.

4. DISCUSSION

Within the framework of the Job Demands–Resources theory, this study contributes to the literature by examining the role of thriving at work as a personal resource in enhancing employees' psychological well-being. The findings indicate that thriving at work, through its vitality and learning dimensions, exerts a significant and positive effect on psychological well-being, which is consistent with prior research (Wei, Ding, & Sun, 2025; Huang & Zhou, 2024). These findings align with the core assumptions of the JD-R theory, suggesting that thriving at work functions as an individual resource through which cognitive and organizational resources play a decisive role in shaping employee outcomes (Bakker & Demerouti, 2007).

While the second assumption of the study proposed that both vitality and learning would have a positive and significant effect on general attitudes toward artificial intelligence, the findings revealed differing effects of the vitality and learning dimensions. Specifically, although the learning sub-dimension of thriving at work had a significant positive effect on attitudes toward artificial intelligence, vitality demonstrated a negative but statistically non-significant effect ($\beta = -0.047$, $p = 0.530$). This non-significant effect represents a theoretically meaningful finding, suggesting that vitality, as an individual resource, does not automatically translate into positive perceptions of artificial intelligence. From the perspective of Self-Determination Theory, although vitality reflects internal energy and aliveness, the development of technology-related attitudes appears to require that this energy be directed toward learning and competence development rather than remaining at an affective level (Deci & Ryan, 2000). In addition, this finding can be further explained through Conservation of Resources Theory, which posits that individuals tend to protect their existing psychological and cognitive resources when confronted with uncertainty or perceived threats (Hobfoll, 1989). Given that artificial intelligence may evoke concerns related to job insecurity, ethical risks, and loss of control, employees with higher vitality may prefer to conserve their personal resources rather than invest them in adopting AI technologies (Hobfoll et al., 2018; Novelli et al., 2024). This resource protection tendency may limit the transformation of vitality into a positive attitude toward artificial intelligence. In contrast, the significant role of the learning dimension indicates that openness to development and skill acquisition enables employees to perceive artificial intelligence more as an opportunity than a threat, thereby fostering more favorable attitudes (Spreitzer et al., 2005; Porath et al., 2012). Overall, this finding suggests that positive attitudes toward artificial intelligence are shaped less by personal energy alone and more by learning-oriented personal resources.

The mediating role of general attitude toward artificial intelligence in the relationship between thriving at work and psychological well-being was examined. The analysis results revealed that thriving at work provides psychological well-being and that general attitude toward artificial intelligence plays a mediating role. This conclusion is consistent with the basic assumptions of JD-R theory. Here, the assumption that individual resources and job resources increase employee motivation and strengthen their well-being is supported (Bakker & Demerouti, 2007). When artificial intelligence is evaluated as a job resource by employees, it can emerge as a development opportunity as a source of vitality and learning. While a positive attitude towards artificial intelligence is important here, it may also be important for employees to adapt their personal resources to a subject of learning. When the level of thriving at work is high, this mediation mechanism can be better supported when artificial intelligence is considered to contribute to the development process as an opportunity rather than a threat.

4. CONCLUSION

In this study, the relationship between thriving at work sub-dimensions and psychological well-being and artificial intelligence general attitude variables was examined based on JD-R theory. Using a longitudinal research method, this study conducted on healthcare workers (nurses) concluded that there is a more meaningful relationship between learning and general attitude toward artificial intelligence and well-being than between learning and vitality. It was also concluded that there is no relationship between thriving and general attitudes toward artificial intelligence. These findings highlight the need for further examination and development of JD-R theory in the context of technology. In particular, there is a need for research on the relationship between personal resources and job demands and resources and how these relationships can be balanced. Additionally, it should not be expected that every employee who feels alive will have a high positive attitude toward artificial intelligence. When employees combine their vitality with learning mechanisms and are open to learning and development processes, this process can reach a more meaningful level. Developing institutional policies in line with this situation could be beneficial for employers.

This research was conducted at two different times. In this context, the data collection time for each variable can be increased. In this respect, it has a limitation. At the same time, the research model can be developed by adding different variables from different sectors, not just healthcare workers. For example, the relationship between vitality and the general attitude mechanism toward artificial intelligence can be examined together with the variables of job meaningfulness and job alienation. Additionally, this model can be re-examined by adding surveys that include positive and negative attitudes toward artificial intelligence, as well as beneficial and risky situations.

This research has original value in terms of the technology-based development of the JD-R theory and the examination of general attitudes toward artificial intelligence, thriving at work, and psychological well-being, which represent important gaps in the existing literature. Beyond its theoretical contributions, the findings offer practical implications for the development of employee-centered technology strategies. In particular, the significant role of the learning dimension of thriving at work suggests that organizations should prioritize learning-oriented approaches when integrating artificial intelligence into work processes. Rather than focusing solely on technological efficiency, institutions are encouraged to design artificial intelligence training programs that enhance employees' learning capabilities, digital competencies, and opportunities for skill development. Structuring artificial intelligence integration processes around continuous learning, participatory training, and hands-on experience may help employees perceive AI as a developmental resource rather than a threat, thereby fostering more positive attitudes toward technology and supporting psychological well-being. In this sense, learning-focused AI implementation strategies can serve as a critical mechanism through which organizations balance technological advancement with employee well-being.

The healthcare sector is characterized by high job demands and intensive use of technology. The findings of this study show that healthcare workers' learning orientations play a critical role in their adoption of artificial intelligence technologies. This situation has important practical implications, especially in the healthcare field, where artificial intelligence applications (e.g., decision support systems, patient monitoring, clinical automation) are becoming widespread. It is believed that it will be important for managers to develop strategies that combine learning with this bias, rather than just focusing on keeping employees engaged, in practice-based processes.

While the present study provides important practical and theoretical contributions, several limitations should be taken into account when interpreting the findings. First, the reliance on self-report measures may limit the extent to which the results reflect actual behaviors and objective outcomes. Future research could enhance the robustness of the findings by incorporating alternative data collection methods, such as supervisor ratings, peer evaluations, or objective performance indicators. Second, the sample was restricted to healthcare professionals (nurses), which may constrain the generalizability of the findings to other occupational groups and sectors. Although the healthcare sector is characterized by high job demands and intensive technology use, future studies are encouraged to test the proposed model across different industries and professional contexts to improve external validity. Third, this study employed a general attitude toward artificial intelligence scale, which does not specifically measure job-specific or task-related perceptions of artificial intelligence. At the time the study was initiated, no Turkish-language attitude measure adapted to the work context and capable of assessing job-related AI perceptions could be identified; therefore, a job-specific artificial intelligence attitude scale was not used. Accordingly, future research would benefit not only from adopting occupation-specific or task-oriented AI attitude measures but also from the development and validation of reliable and valid measurement instruments to address the assessment of artificial intelligence use in work-life contexts. Addressing these limitations would enable a more comprehensive understanding of the role of artificial intelligence in employee well-being and further contribute to the advancement of the JD-R framework in technology-driven work settings.

Disclosure Statements

1. The author of this article confirm that their work complies with the principles of research and publication ethics. In this study, ChatGPT and DeepL were used as supportive tools during the language editing and translation processes. These tools were employed solely for linguistic improvement purposes, and the final responsibility for the accuracy of the content and meaning rests with the author. In addition, supportive tools were used during the reference-checking process, and the accuracy and appropriateness of all references were verified by the author.

2. No potential conflict of interest was reported by the author.

3.This article was screened for potential plagiarism using a plagiarism screening program.

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