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# THE MODERATING ROLE OF GENERAL ATTITUDE TOWARD ARTIFICIAL INTELLIGENCE IN THE EFFECT OF JOB STRESS ON PROACTIVE BEHAVIOR

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## Abstract

The aim of this study is to examine the moderating role of general attitude toward artificial intelligence in the effect of job stress on proactive behavior, based on Affective Events Theory. The sample of the study consisted of healthcare professionals. The data were collected at two different times using a convenience sampling method and a longitudinal research design; data from 205 participants were analyzed using simple linear regression and the PROCESS Macro (Model 1). The results of the analysis showed that general attitude toward artificial intelligence had a moderating role in the relationship between job stress and proactive behavior. This study contributes to the development of Affective Events Theory through an AI-based theoretical perspective. Another original aspect of this study is the use of an artificial intelligence-based analysis approach. In this respect, the study further contributes by comparing the results of traditional analysis methods with those of artificial intelligence-based approaches.

***Keywords:*** *Affective Events Theory, Job Stress, General Attitude Toward Artificial Intelligence, Proactive Behavior*
***JEL Classification:*** *L2, M19, M54*

# İŞ STRESİNİN PROAKTİF DAVRANIŞ ÜZERİNDEKİ ETKİSİNDE YAPAY ZEKÂ GENEL TUTUMUN MODERATÖR ROLÜ

## Öz

Bu çalışmanın amacı, Duygusal Olaylar Teorisi temelinde iş stresinin proaktif davranış üzerindeki etkisinde yapay zekâya yönelik genel tutumun moderatör rolünü incelemektir. Araştırmanın örneklemini sağlık çalışanları oluşturmaktadır. Veriler, kolayda örneklem yöntemi, boylamsal veri toplama tasarımı benimsenerek iki farklı zamanda toplanmış, elde edilen 205 katılımcıdan gelen veriler basit doğrusal regresyon, PROCESS Macro (Model 1) ile analiz edilmiştir. Analiz sonuçları, yapay zekâya yönelik genel tutumun iş stresi ile proaktif davranış arasındaki ilişkide moderatör rolü üstlendiğini göstermiştir. Bu çalışma, Duygusal Olaylar Teorisi'nin yapay zekâ temelli teorik bir bakış açısıyla geliştirilmesine katkı sağlamaktadır. Bir diğer özgün yönü ise, araştırmada yapay zekâ temelli bir analiz yaklaşımı kullanılmış olmasıdır. Bu yönüyle bu araştırma, geleneksel analiz yöntemlerinin sonuçlarıyla yapay zekâya dayalı analiz yaklaşımlarının karşılaştırılmasına da katkı sağlamaktadır.

***Anahtar Kelimeler:*** *Duygusal Olaylar Teorisi, İş Stresi, Yapay Zekâ Genel Tutum, Proaktif Davranış*
***JEL Sınıflandırması:*** *L2, M19, M54*

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## 1. Introduction

Modern organizations emphasize proactive behaviors such as planning and executing tasks, solving work-related problems, improving work processes, creating opportunities, and taking personal initiative (Bekar, 2022). According to Crant (2000: 436), proactive behavior can be defined as actions aimed at improving current work conditions, developing new ones, and actively organizing and transforming the environment rather than reacting to it. One of the important factors influencing proactive behavior is work stress. According to some studies, work stress has a negative effect on proactive behavior (Li & Guo, 2021); however, other studies suggest that work stress can enhance proactive behavior and lead to greater employee productivity (Grant & Ashford, 2008). Findings from the American Institute of Stress, based on the Headspace 2024 *Workforce State of Mind* report, reveal that 47% of work stress originates from the workplace, and 77% of work-related stress negatively affects employees' mental health. This study primarily seeks to answer the question: How does work stress affect proactive behavior? This question is examined through the lens of Affective Events Theory (AET). According to Affective Events Theory developed by Weiss and Cropanzano (1996), negative work events can generate negative emotions, which in turn may lead to adverse work outcomes. In this context, work stress can serve as a triggering factor for the emergence of negative emotions. Consequently, employees who display lower levels of proactive behavior may create undesirable situations for organizations (Li & Guo, 2021). Therefore, this study focuses on testing the hypothesis that work stress negatively and significantly affects proactive behavior.

Secondly, this research examines AI-based attitudes as antecedents of proactive behavior. On August 1, 2024, the "European Artificial Intelligence Act" came into force, aiming to regulate, distribute, and promote the development of artificial intelligence across the European Union. In the healthcare field, artificial intelligence has been applied in various areas, including disease diagnosis, data clustering, and the analysis and interpretation of patient information. According to this law, a wide range of regulations have been introduced, including measures aimed at reducing the risks associated with high-risk software designed for medical purposes, ensuring high-quality datasets, providing clear user information, and maintaining human oversight. In Turkey, the artificial intelligence market is projected to grow by 28.72% between 2024 and 2030. In a global comparison, the largest market size is expected to be in the United States, amounting to $50.16 billion in 2024 (Statista, 2024). In this context, artificial intelligence is expected to become one of the most significant technological tools of both the present and the future.

Thirdly, this research focuses on the moderating role of general attitude towards artificial intelligence in the relationship between job stress and proactive behavior. With the integration of artificial intelligence into business life, employee behaviors are reshaped and can be one of the important issues to be examined in order to provide a better work environment in the future. In fact, one of the pressures experienced by employees may stem from technology-related stress. Employees may also experience stress due to a lack of knowledge or skills regarding the use of new technologies (Zhang et al., 2025). Employees' attitudes toward technology can also influence their level of proactivity (Sun et al., 2025). In this context, the research investigates the following question: How does the general attitudes toward artificial intelligence shape the relationship between job stress and proactive behavior?

While developments based on artificial intelligence have gained significant momentum, there is a need to examine the relationships between among these variables, as only a limited number of studies have been conducted in this field. Therefore, this research has original value in addressing the general attitude toward artificial intelligence (GATAI) as a moderating variable. There is no other study based on this model in which these variables have been examined together. At the same time, this research has original value in contributing to the development of AET through an artificial intelligence (technology)-based study, revealing the extent to which job stress conditions in the healthcare sector are balanced with artificial intelligence and how this affects proactive behavior. Another unique contribution of this research lies in its methodological approach. Specifically, the study demonstrates how to analyze datasets using artificial intelligence – based methods and compare the results with traditional analytical techniques.

## 2. Theoretical Framework and Hypotheses

The Affective Events Theory developed by Weiss and Cropanzano (1996) explains, by modeling, how events and situations that occur in the workplace shape the emotional processes of employees and how these emotions are transformed into attitudes and behaviors. It is assumed that positive work events, such as rewards, lead to positive emotions, and at the end of the process, attitudes and behaviors that increase job satisfaction and performance can be formed. On the contrary, in processes such as punishment, employees experience negative emotional states and may show low job satisfaction and performance (Mitchell, 2011).

Job stress appears as a psychological reaction that emerges as a result of the emotions employees develop in response to stressors in the work environment, based on the AET (see Fuller et al., 2003; Liu et al., 2021). Such reactions occur when individuals experience a mismatch between the demands of the work environment and their coping abilities, leading to emotional and physiological responses (Lazarus & Folkman, 1984). For instance, Friori, Bollmann, and Rossier (2015) found that negative emotions are associated with higher levels of job stress, whereas positive emotions are linked to lower levels of job stress.

Job stress can be one of the important antecedents affecting proactive behavior. To briefly explain, proactive behavior refers to actions that employees take to anticipate future situations in ways that influence both their environment and themselves (Grant & Ashford, 2008). Proactive behavior has been studied across a wide range of subjects and fields, including interpersonal proactive behavior (Warshawsky et al., 2012), proactive socialization behavior (Nie et al., 2022), proactive performance (Cullen-Lester et al., 2016), and proactive motivation (Zhang & Inness, 2019). In this research, we focus on unit-oriented proactive behavior, which was examined by Wu et al. (2018). Unit-oriented proactive behavior refers to the extent to which an employee contributes to the success of their unit, improves it, and moves business activities forward (Wu et al., 2018).

In the literature, different views exist regarding the relationship between job stress and proactive behavior. While Grant and Ashford (2008) stated that stress can act as a motivating factor that enhances proactive behavior, Li and Guo (2021) found a negative relationship between hindrance-type stress, a form of stress that prevents individuals from achieving growth and goals, and proactive behavior. Based on the AET, stress can be viewed as a negative psychological and physiological reaction developed by employees. Accordingly, it is assumed that under stress, employees tend to behave less proactively. Therefore, the first hypothesis of this research is formulated as follows.

H1. Job stress has a significant negative effect on proactive behavior.

Artificial intelligence is being developed and has become influential in almost all sectors worldwide. The foundations of artificial intelligence were laid by Alan Turing in the 1950s, and it entered the philosophical literature with the first article he published, which posed the question "Can machines think?" (Mays, 1959).

According to Mijwel (2015), the origins of artificial intelligence date back to the Ancient Age, when Alexander Heron designed mechanical automata powered by water and steam. These developments have continued to the present day, with the establishment of Google's first artificial intelligence laboratory in Ghana in 2019. Artificial intelligence, which has led to different developments in various fields over the years, is essentially defined as "the ability of a computer, a computer-controlled robot, or a programmable device to perform functions such as perception, learning, reasoning, decision-making, problem-solving, and communication in a human-like manner," according to the Türk Dil Kurumu (2025). Similarly, Hughes et al. (2019) define artificial intelligence as the ability of a computer system to perceive its environment, reason, and respond.

Research on general attitudes toward artificial intelligence examines individuals' perceptions of the integration of AI technologies into daily and business life, as well as their expectations, emotional reactions, and behavioral tendencies related to AI (see Schepman & Rodway, 2020; Grassini, 2023; Satici et al., 2025). The use of AI in the workplace can encourage employees to display proactive behavior. Du et al. (2024) conducted a study in China using data from 203 participants collected over two time periods and found that employees' attitudes toward AI were positively related to proactive behavior. Similarly, Ding et al. (2025), in a study conducted in China with data obtained from 587 participants, found that the use of AI increases motivation toward AI usage, which in turn has a positive and significant effect on proactive behavior.

In light of these findings, the second hypothesis of this research is presented below:

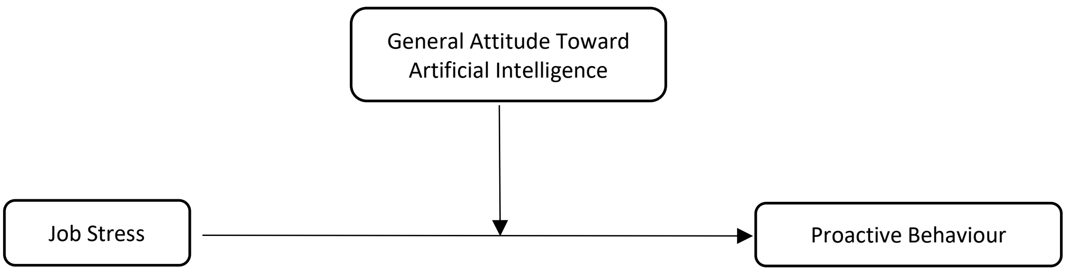
H2. General attitude toward artificial intelligence has a significant and positive effect on proactive behavior.

Bekar (2022: 13) presented detailed information based on the model of AET in this study. Within the framework of this model, the characteristics of the work environment shape work events; work events shape emotions; and emotions, in turn, shape behaviors and attitudes. as stress can act as a catalyst for work-related behaviors and may influence proactive behavior processes (Ohly et al., 2006). Proactive behavior is regarded as judgment-based behavior and is treated as an outcome variable. The GATAI is examined through the tendency dimension, as in new job design processes, artificial intelligence can be a factor that enhances proactive behaviors by facilitating employees' work styles (Parker & Grote, 2022). Based on the AET, it is assumed that a GATAI may weaken and reshape the negative effect of job stress on proactive behavior (Qin et al., 2025). This assumption is grounded in the idea that a positive attitude toward artificial intelligence, along with facilitating factors such as problem-solving and quick decision-making, can reduce the negative impact of stress and contribute to more proactive employee behavior.

In this context, the last hypothesis of the research is presented below. The model of the research is shown in Figure 1.

H3. The general attitude toward artificial intelligence has a moderating effect on the relationship between job stress and proactive behavior.

Figure 1: **Research Model**




## 3. Methodology of the Research

A quantitative research method was employed in this study. The data were collected using a longitudinal data collection design. The first wave of data was collected in April 2025, during which information on job stress (the independent variable) was obtained. At least three weeks later, the second wave of data was collected, including measures of GATAI (the moderator variable) and proactive behavior (the dependent variable). During the data collection process, participants were asked to generate a personal code consisting of the initials of their first and last names combined with the last two digits of their phone number. Alternatively, if they had no a personal nickname, they were asked to incorporate it into the code (for example, FB-61 or FG-38). These codes were then used to match the two waves of data. At the end of the matching process, data from 205 participants were successfully paired. According to Kotrlik and Higgins (2001), a sample size of 205 is adequate for studies utilizing a longitudinal data collection method. After data matching, IBM SPSS Statistics v.22 was used to conduct simple linear regression analyses, and PROCESS Macro v.3 was used to examine moderating effects. Additionally, AMOS v.23 was employed for confirmatory factor analysis (CFA).

The sample of this study consists of healthcare professionals. Healthcare workers were selected because they are among the occupational groups experiencing high levels of job stress due to long working hours, heavy patient loads, frequent exposure to death, and emotional exhaustion (Shanafelt et al., 2012). Another reason for selecting healthcare professionals is that they tend to exhibit proactive behaviors, including the ability to make quick decisions, anticipate situations, and take preventive actions. Artificial intelligence can provide supportive information in the processes of disease diagnosis and treatment within the healthcare field and may act as a stress-reducing factor. Moreover, AI is expected to become an essential element in the future of the healthcare sector (Jiang et al., 2017). Considering the recent developments in artificial intelligence, the healthcare sector represents a suitable and meaningful context for this research. A convenience sampling method was adopted to collect data, as it offers practical advantages in terms of cost, accessibility, time, and organizational feasibility (Creswell, 2013).

### 3.1. Participants and Procedures

The research was initiated with the approval numbered E-95674917-108.99-322070 from the Scientific Research and Publication Ethics Committee of the University. A total of 205 healthcare professionals participated in the study across two data collection phases. In the first wave, data were obtained from 450 participants, and in the second wave, from 350 participants. After matching the two datasets based on participants' identification codes, 205 complete and valid responses were retained for the final analysis.

As a result of the two data collection phases, a total of 205 participants were included in the study. Of these, 29.3% (n = 60) were male and 70.7% (n = 145) were female. Among the occupational groups in the healthcare sector, 49.8% (n = 102) were nurses, who constituted the majority of the sample. The mean age of the participants was 29.35 years (SD = 0.46; range = 20–68). More than half of the participants (55.6%, n = 114) held an undergraduate degree. Participants had been working in their current workplace for an average of 4.37 years (SD = 4.68; range = 1–25), and their average total work experience was 6.09 years (SD = 0.46; range = 1–43). Additionally, 71.2% (n = 146) of the participants reported having no prior experience with artificial intelligence. The socio-demographic characteristics of the participants are presented in Table 1.

Table 1: **Sociodemographic Characteristics of Participants**

| Variables | | N | % |
|---|---|---|---|
| **Gender** | Male | 60 | 29.3 |
| | Woman | 145 | 70.7 |
| **Marital Status** | Married | 83 | 40.5 |
| | Single | 121 | 59.0 |
| | Other (Divorced etc.) | 1 | 0.5 |
| **Profession** | Nurse | 102 | 49.8 |
| | Medical Secretary | 62 | 30.2 |
| | Midwife | 17 | 8.3 |
| | Other (Specialist, doctor, physiotherapist, etc.) | 24 | 11.7 |
| **Education** | High school and equivalent | 12 | 5.9 |
| | Associate degree | 69 | 33.7 |
| | License | 114 | 55.6 |
| | Postgraduate | 10 | 4.9 |

Table 1 (Continued): **Sociodemographic Characteristics of Participants**

| Variables | | N | % |
|---|---|---|---|
| **Age** | 18-25 age range | 73 | 35.6 |
| | 26 - 35 age range | 99 | 48.3 |
| | 36 - 45 age range | 24 | 11.7 |
| | 46 - 55 age range | 7 | 3.4 |
| | 56 and above | 2 | 1.0 |
| **Duration of employment at current workplace** | 1 to 5 years | 158 | 77.1 |
| | 6 to 10 years | 29 | 14.1 |
| | 11 to 15 years | 7 | 3.4 |
| **Duration of employment at current workplace** | 16 to 20 years | 8 | 3.9 |
| | Between 21 and 25 years | 3 | 1.5 |
| **Total work experience** | 1 to 5 years | 131 | 63.9 |
| | 6 to 10 years | 40 | 19.5 |
| | 11 to 15 years | 16 | 7.8 |
| | 16 to 20 years | 7 | 3.4 |
| | 21 and above | 11 | 5.4 |
| **Use of AI** | Yes | 59 | 28.8 |
| | No | 146 | 71.2 |
| **Total** | | **205** | **100** |

### 3.2. Measures

**Job stress:** The items of the job stress scale are based on the doctoral dissertation of Parasuraman (1977) and later adapted into Turkish by Okan and Özbek (2016), drawing on the work of Sosik and Godshalk (2000). In the present study, job stress was measured using the version of the scale adapted by Okan and Özbek (2016). The participants responded to 7 items using a 5-point Likert-type scale ranging from 1 (Never) to 5 (Always). The Cronbach's alpha coefficient for the question items of job stress varies between 0.556 and 0.841. There are 7 question items in total.

**Proactive behavior:** The items measuring unit-oriented proactive behavior, originally developed by Griffin et al. (2007) and later used by Wu et al. (2018), were employed in this study. The scale was adapted into Turkish by Bekar (2022) in his unpublished doctoral dissertation. The present research is also based on Bekar's (2022) work, which examined three different samples — healthcare professionals, furniture workers, and academicians. Within the scope of the current study, participants responded to 3 items using a 7-point Likert-type scale, ranging from 1 (Strongly Disagree) to 7 (Strongly Agree). The Cronbach's alpha coefficients reported by Bekar (2022) were 0.949 for healthcare professionals, 0.885 for furniture workers, and 0.954 for academicians, indicating high internal consistency across all samples.

***General attitude toward artificial ıntelligence (GATAI) scale short form*:** The short form of the General Attitude Toward Artificial Intelligence (GATAI) Scale developed by Batuk et al. (2024) was used in this study. The scale consists of 4 items, and the Cronbach's alpha coefficient reported by the authors is 0.89, indicating high internal consistency reliability. Participants were asked to indicate their attitudes toward artificial intelligence tools (e.g., ChatGPT, QuillBot, Elicit, Scite AI) using a 10-point Likert-type scale, ranging from 1 (Strongly Disagree) to 10 (Strongly Agree).

### 3.3. Common Method

In this study, data were collected across two time periods. Recent research recommends collecting data at different time points to minimize potential bias. Ideally, data should be gathered at three separate time intervals; however, in this study, data could only be obtained at two time points. Under such circumstances, the common method bias (CMB) problem may arise. To assess this issue, Harman's one-factor test was conducted. The results indicated that the first factor explained 37.237% of the total variance. Since this value is below the 50% threshold, it can be concluded that common method bias was not a significant concern in this study (Fuller et al., 2016; Rather et al., 2023).

### 3.4. Reliability - Validity

To assess construct validity, a confirmatory factor analysis (CFA) was conducted by loading a total of 14 items representing job stress, proactive behavior, and general attitude toward artificial intelligence (GATAI) into a single-factor model. The analysis was performed using the AMOS v.23 software package. The results for the single-factor model were as follows: $\chi^2$ (77, $N$ = 205) = 2786.08, $\chi^2$/df = 36.18, AGFI = 0.15, CFI = 0.33, TLI = 0.21, RFI = 0.20, $p < 0.001$, RMSEA = 0.42, SRMR = 0.32. It is an expected result that the fit indices are not at the desired level when all items are loaded onto a single factor, as the variables theoretically represent distinct constructs (see Özbek, 2011). In the second stage, a three-factor model was tested by separating the items into their respective constructs: job stress, proactive behavior, and general attitudes towards AI. The results were: $\chi^2$ (74, N = 205) = 315.59, $\chi^2$/df = 4.27, AGFI = 0.77, CFI = 0.95, TLI = 0.93, RFI = 0.91, $p < 0.001$, RMSEA = 0.13, SRMR = 0.04. A modification index suggested a covariance between Job Stress Item 1 and Job Stress Item 2, which was added to the model. The modified three-factor model demonstrated improved fit indices: $\chi^2$ (73, N = 205) = 202.43, $\chi^2$/df = 2.77, AGFI = 0.82, CFI = 0.97, TLI = 0.96, RFI = 0.94, $p < 0.001$, RMSEA = 0.09, SRMR = 0.04. These results indicate that the final model achieved acceptable to excellent fit indices, based on the criteria suggested by Hu and Bentler (1999) and Kline (2016). The three-factor structure indicates that the constructs are theoretically distinct and the measurement model demonstrates good construct validity. The detailed CFA results are presented in Table 2.

Table 2: **Confirmatory Factor Analysis Results**

| Variables | $x^2$/df | RMSEA | AGFI | CFI | TLI | RFI | SRMR |
|---|---|---|---|---|---|---|---|
| **Model 1 (Single Factor)** | 36.18 | 0.42 | 0.15 | 0.33 | 0.21 | 0.20 | 0.32 |
| **Model 2 (3 Factors)** | 4.27 | 0.13 | 0.77 | 0.95 | 0.93 | 0.91 | 0.04 |
| **Model 3 (Modified 3 Factors)** | 2.77 | 0.09 | 0.82 | 0.97 | 0.96 | 0.94 | 0.04 |

Table3: **Exploratory Factor Loadings of Variables**

| Items | Factor Loadings | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | AVE | CR | Alpha |
| **S1** | 0.85 | | | 0.77 | 0.95 | 0.95 |
| **S2** | 0.89 | | | | | |
| **S3** | 0.91 | | | | | |
| **S4** | 0.92 | | | | | |
| **S5** | 0.78 | | | | | |
| **S6** | 0.90 | | | | | |
| **S7** | 0.89 | | | | | |
| **PB1** | | 0.95 | | 0.93 | 0.98 | 0.97 |
| **PB2** | | 0.98 | | | | |
| **PB3** | | 0.96 | | | | |
| **GATAI1** | | | 0.97 | 0.99 | 0.95 | 0.97 |
| **GATAI2** | | | 0.98 | | | |
| **GATAI3** | | | 0.98 | | | |
| **GATAI4** | | | 0.97 | | | |

**Note:** S: Job Stress, PB: Proactive Behavior, GATAI: General Attitude Toward Artificial Intelligence

Exploratory factor analysis was also conducted for construct validity in this research model obtained by using different variables. In order to determine whether the data were suitable for factor analysis, the following steps were followed: 1) Barlett's test and Kaiser-Meyer-Olkin (KMO) sample adequacy criterion) test, 2) obtaining factors, 3) factor rotation, 14 and naming the factors appropriately (Thompson, 2004; Kalayci, 2010: 321-323). The results of the factor analysis are presented in Table 3. Based on the Principal Components Analysis (PCA) and using the Direct Oblimin rotation method, the variables were divided into three distinct factors. The results of the KMO and Bartlett's tests showed a KMO value of 0.85 and an Approx. Chi-Square value of 4023.98 (df = 91, p < 0.001), indicating that the data were suitable for factor analysis. The factor loadings, total variances explained, and KMO values were found to be within acceptable limits. Additionally, convergent validity and internal consistency analyses were conducted using Average Variance Extracted (AVE) and Composite Reliability (CR) to further assess the validity and reliability of the measurement model. Here, AVE value of job stress is 0.77 and CR value is 0.95; AVE value of proactive behavior variable is 0.93 and CR value is 0.98; AVE value of GATAI variable is 0.99 and CR value is 0.95. AVE value is above 0.50 and the CR value is above 0.70, the CR value is greater than the AVE value. As a result of the results obtained, it is shown that construct validity is found for this model (Hair et al., 2010). The results of the analysis are presented in Table 3.

Table 4 presents the means, standard deviation and correlation analysis results of the variables of the study.

Table 4: **Correlation Analysis of Variables**

| Variables | M | SD | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Gender** | 1.71 | 0.46 | 1 | | | | | | | | | |
| **Age** | 1.85 | 0.83 | -.25*** | 1 | | | | | | | | |
| **Education** | 2.56 | 0.67 | .15* | .11 | 1 | | | | | | | |
| **Marital Status** | 1.41 | 0.50 | -.17* | .53** | -15* | 1 | | | | | | |
| **CES** | 1.39 | 0.85 | -.18* | .65** | .00 | .43** | 1 | | | | | |
| **TES** | 1.67 | 1.11 | -.12 | .76** | .06 | .52** | .78** | 1 | | | | |
| **AI Experience** | 1.71 | 0.45 | -.05 | -.14 | -.11 | -.01 | -.07 | -.05 | 1 | | | |
| **Job Stress** | 2.50 | 1.14 | -.03 | -.06 | .13 | -.09 | -.14* | -.07 | .06 | 1 | | |
| **Proactive Behavior** | 5.07 | 1.85 | -.03 | .17* | -.05 | .12 | .07 | .11 | -.12 | -.03 | 1 | |
| **GATAI** | 5.95 | 2.97 | -.02 | .01 | .09 | .06 | -.05 | -.12 | -.20** | .09 | .47** | 1 |

**Note:** M: Mean, SD: Standard Deviation, CES: Working time at current workplace, TES: Total working time at workplace, GATAI: General Attitude Toward Artificial Intelligence**.**

### 3.5. Hypothesis Testing

#### 3.5.1. Simple Linear Regression Analysis Results

To test Hypothesis 1, a simple linear regression analysis was conducted. Here, the relationship between job stress (independent variable) and proactive behavior (dependent variable) was tested. As a result of the analysis, it was found that there was a negative relationship between the two variables, but since p > 0.05, it was found that there was no significant relationship between the two variables (β= -0.08, p= 0.21). Therefore, H1 is rejected (see, Kalaycı, 2010). It was concluded that there was a positive and significant relationship between GATAI and proactive behavior (β= 0.48, p= 0.000). Therefore, H2 is accepted. Table 5 shows the results of Simple Linear Regression Analysis.

Table 5: **Results of Simple Linear Regression Analysis**

| **Independent Variable** | **Dependent Variable Proactive Behavior Model 1** | |
|---|---|---|
| | **ß** | **t** |
| **Constant** | | 10.44*** |
| **Job Stress** | -0.08 | 7.77 |
| **GATAI** | 0.48 | -1.25*** |

**Notes:** ***p<0.001, **p<0.01, *p<0.05, $R^2$: 0.23, R: 0.48, F:30.29, N:205, GATAI: General Attitude Toward Artificial Intelligence.

### 3.5.2. Moderation Effects

The PROCESS Macro (v.3.4) was used to examine the moderating role of General Attitude Toward Artificial Intelligence (GATAI) in the relationship between job stress and proactive behavior. After applying Model 1 with 5,000 bootstrap samples and 95% percentile bootstrap confidence intervals (CIs), the moderation analysis was conducted. The results indicated that all variables together explained 25% of the variance in the outcome variable ($R^2 = 0.25$). The interaction effect between job stress and GATAI was found to be significant (b = 0.09, 95% CI [0.02, 0.15], t = 2.53, p = 0.012). Since the lower and upper limits of the confidence interval did not include zero, this result confirms the significance of the interaction effect (Gürbüz, 2019; Bozkurt, 2023). Therefore, Hypothesis 3 which posits that GATAI has a moderating effect is supported.

According to the conditional effects analysis, when GATAI is low (b = -0.50, 95% CI [-0.84, -0.15], t = -2.81, p < 0.01), the relationship between job stress and proactive behavior is negative and significant. When GATAI is moderate (b = -0.06, 95% CI [-0.27, 0.14], t = -0.61, p = 0.54), the relationship is negative but not significant. When GATAI is high (b = 0.11, 95% CI [-0.16, 0.38], t = 0.81, p = 0.42), the relationship becomes positive but not significant.

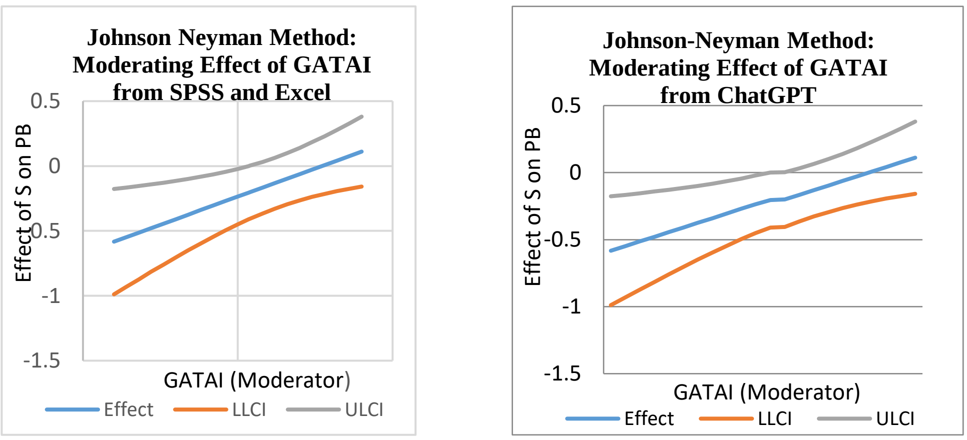
These results indicate that as the positive attitude toward AI increases, the negative relationship between job stress and proactive behavior weakens and may even become positive. This finding supports the moderating role of GATAI in the relationship between job stress and proactive behavior. Table 6 presents the detailed results of the moderation analysis.

Table 6: **The Moderation Role of GATAI in The Relationship Between Job Stress and Proactive Behaviour**

| Model 1 | B | S.E. | t | F | R | $R^2$ |
|---|---|---|---|---|---|---|
| **Constant** | 4.87*** [3.67, 6.07] | 0.61 | 8.02 | 22.87 | 0.50 | 0.25 |
| **S (X)** | -0.67 [-1.14,-0.20] | 0.24 | -2.83 | | | |
| **GATAI (W)** | 0.07 [-.08, .27] | 0.09 | 1.03 | | | |
| **S*GATAI** | 0.09* [.02, .15] | 0.03 | 2.53 | | | |

**Notes**: ***p<0.001, **p<0.01, *p<0.05, [ ]: Values in parentheses are confidence intervals, B: Unstandardized beta coefficients are reported, S.E. = Standard error; t = t-value; F = F-statistic; R = Multiple correlation coefficient; $R^2$: Coefficient of determination, S: Job stres, GATAI: General attitude toward artificial intelligence.

Figure 2: **Graphing of Analysis Results with SPSS and Artificial Intelligence (ChatGPT)**




Graphical values were obtained using the Johnson–Neyman method based on the SPSS program. These values were then exported to Excel and visualized accordingly. The graphical representation procedure was based on Bozkurt (2023, pp. 136–138). To generate an additional visualization incorporating artificial intelligence, a graph based on the Johnson–Neyman method was created using a prompt written in ChatGPT. The comparison between the two visualizations is presented in Figure 2. The first figure illustrates the visualization created in Excel using the SPSS output, whereas the second figure presents the visualization generated by ChatGPT based on the Johnson–Neyman analysis.

### 3.5.3. Analysis Results with Artificial Intelligence

The research results were also analyzed using ChatGPT, one of the advanced artificial intelligence-based analytical tools. For this purpose, the "Statistics File Reader" interface, developed by Said Sürücü (Artificial Intelligence Expert), was accessed.

The analysis was conducted by uploading the dataset in .sav (SPSS) format to the interface. A structured prompt-based command was then executed to replicate the regression analysis process. The following command was used:

> *"Define the data file. First, consider the variables of job stress (S) and GATAI as independent variables and examine their effects on proactive behavior (PD) using simple linear regression analysis. Report the standardized beta coefficient (β), p-value, and R-squared (R²) value."*

ChatGPT processed the dataset, automatically performed the regression analysis, and generated statistical outputs including coefficients, significance levels, and explained variance. These outputs were subsequently compared with those obtained from IBM SPSS Statistics v.22 to evaluate the accuracy and consistency of the AI-based analysis.

As shown in Table 7, the standardized coefficients, p-values, and $R^2$ values are presented. The results indicate that job stress has a negative but non-significant effect on proactive behavior, whereas general attitude toward artificial intelligence (GATAI) has a positive and statistically significant effect. According to the artificial intelligence–based analysis, the output was interpreted as follows: "$R^2$ = 0.23, the model explains 23% of the variance in proactive behavior." Furthermore, the AI-generated interpretation stated that: "GATAI has a strong, positive, and statistically significant effect on proactive behavior (β=-0.08, p=0.21), whereas job stress does not have a significant effect (β=0.48, p < .001)."

Table 7: **Artificial Intelligence Based (ChatGPT) Regression Analysis Results**

| Dependent Variable (PB) | β | P - Value | R² |
|---|---|---|---|
| **S** | -0.08 | 0.21 | 0.23 |
| **GATAI** | +0.48 | < 0.001 | |

**Notes:** β: Unstandardized beta coefficients are reported, S: Job stres, GATAI: General attitude toward artificial intelligence, PB: Proactive behavior.

Secondly, the following prompt was used: "In the second step, analyze the moderating role of GATAI in the effect of job stress on proactive behavior using PROCESS Macro Model 1. Briefly report the results." The analysis results obtained from this command are presented in Table 8.

Table 8: **Interaction Term Results (S × GATAI)**

| Interaction Term | β | P - Value | Significance Status |
|---|---|---|---|
| **S*GATAI** | 0.09 | 0.01 | Significance (p < .05) |

**Notes:** β: Unstandardized beta coefficients are reported, S: Job stres, GATAI: General attitude toward artificial intelligence.

Table 9: **Conditional Effects the Focal Predictor at Values of the Moderator by AI**

| GATAI (Moderator) | Impact of S on PB | SE | t | p | LLCI | ULCI | Comment |
|---|---|---|---|---|---|---|---|
| **Low (2.98)** | –0.41** | 0.15 | –2.74 | 0.01 | –0.70 | –0.12 | Significant negative impact |
| **Medium (5.95)** | –0.15 | 0.10 | –1.54 | 0.13 | –0.35 | 0.04 | Not significant |
| **High (8.91)** | +0.10 | 0.14 | 0.77 | 0.44 | –0.16 | 0.37 | Not significant |

**Notes:** GATAI: General attitude toward artificial intelligence, S: Job stress, PB: Proactive behavior; SE: Standard error, t = t-value, p = Significance level, LLCI: Lower limit of 95% confidence interval; ULCI: Upper limit of 95% confidence interval, Comment: Interpretation of the effect.

Table 9 shows the conditional effect of general attitude towards AI on the impact of job stress on proactive behavior. Table 9 reports the ChatGPT results. At the last stage, conditional effect values were requested. This value is important for presenting the graphs of the variables. The following output was obtained.

**4. Conclusion**

In this research, proactive behavior (unit-oriented proactive behavior), which is one of the important issues in organizational behavior and has been extensively studied in recent years, is discussed as an outcome variable. Employees' proactive behavior is a desirable situation for employers, institutions, and organizations. In the literature, the focus is generally on why employees do not behave proactively, and various suggestions have been developed to enhance proactive behaviors. In this context, the results of an analysis conducted on two-wave data collected from 205 participants in the health sector are presented. Job stress is considered an antecedent variable of proactive behavior, and the relationship between job stress and proactive behavior is examined based on Affective Events Theory. Although some studies suggest that job stress increases proactive behavior (Grant & Ashford, 2008), others argue that job stress is negatively related to proactive behavior (Li & Guo, 2021). In this study, it was assumed that there would be a negative and significant relationship between job stress and proactive behavior; however, the analysis results revealed an unexpected finding. A negative relationship was found between job stress and proactive behavior, but this relationship was not statistically significant**.** In this respect, the findings are consistent with those of Zhou et al. (2025). This study provides a perspective for further examining and investigating the relationship between job stress and proactive behavior.

Secondly, the effect of GATAI on proactive behavior was examined. As a result of the study, it was found that GATAI positively and significantly affected proactive behavior. In this respect, the findings of this study are consistent with the results presented by Du et al. (2024) and Ding et al. (2025).

Thirdly, the moderating role of GATAI in the relationship between job stress and proactive behavior was examined. In the relationship between these three variables, where the original value of the research was presented, The findings, which represent the original contribution of this research, revealed that the negative effect of job stress decreases and weakens when individuals hold a positive attitude toward artificial intelligence. As a result of the Johnson-Neyman analysis, it was found that the relationship between job stress and proactive behavior became more positive among individuals with higher levels of GATAI.

This shows that when emerging technologies are considered as a supportive tool rather than a threat, employees contribute to the development of their units and follow a solution-oriented approaches even under stressful conditions. Furthermore, these findings indicate that technological adaptation is not solely a technical process but also a psychological one, as emphasized by Schepman and Rodway (2020) in their study developing a scale to measure attitudes toward artificial intelligence. Theoretically considered, this event strengthens the basic assumption of the AET. Stressors encountered in the work environment influence individuals' tendencies, which in turn shape their behaviors. The negative impact of job stress is moderated by employees' general attitudes toward artificial intelligence. In other words, when employees hold positive attitudes toward artificial intelligence, the adverse effects of job stress stemming from employees' perceptions and attitudes are reduced, and as a result, proactive behavior is maintained rather than diminished.

The findings of the research offer important practical implications for managers and organisations. It has been found that the negative consequences of stress can be reduced with artificial intelligence tools, and that employees' proactive behaviour will be supported. The results demonstrate that technological adaptation is not only related to technical processes but also to emotional and cognitive processes, thereby making a meaningful contribution to the organisational behaviour literature.

In this context, training programmes, awareness initiatives and participatory technological transformation processes should be designed to strengthen employees' positive attitudes towards artificial intelligence. This approach will help reduce the negative effects of work-related stress and enable employees to keep up their proactive behaviour. Furthermore, it is important for managers to adopt leadership styles that support stress management and psychological resilience. Organisations should develop organisational cultures that encourage new technologies to be perceived as supportive tools rather than threats. In future-oriented research, if these conditions are met, it will be important to include the topics of organisational culture and job meaningfulness in the research model and to conduct research at the organisational level. In this process, where artificial intelligence is still at a developmental stage, the resistance shown by employees to change will also be among the important topics to be examined in future-oriented research. For the future, it is suggested to test this research with different variables such as career-oriented proactive behavior, interpersonal proactive behavior, proactive socialization behavior, proactive performance, and proactive motivation. At the same time, a new research model that addresses negative attitudes based on artificial intelligence will contribute to the further development of AET.

The final original contribution of this study lies in the potential to test its methodology using artificial intelligence tools and to compare the outcomes derived from traditional statistical techniques with those obtained through AI-based analytical methods. Although the analyses conducted with artificial intelligence produced results largely consistent with those obtained via SPSS, the findings indicate that further methodological refinement is still required. Nevertheless, artificial intelligence represents a promising avenue for researchers, offering valuable support in data interpretation, enhancing analytical precision, and guiding future academic investigations.

This study has certain limitations. In particular, the use of a convenience sampling method restricts the generalizability of the findings. In future research, the study could be replicated by using different data collection methods, additional data time process, or by incorporating new variables to obtain more comprehensive results.

**Ethical Statement**

The research was initiated with the approval numbered E-95674917-108.99-322070 obtained from the Scientific Research and Publication Ethics Committee of the Gumushane University.

In this study, AI-assisted analyses were conducted using ChatGPT. Both AI-based tools (ChatGPT and DeepL) and expert support were utilized during the second phase for English translation and language editing. All outputs were reviewed by the author to ensure accuracy and maintain academic integrity. The use of artificial intelligence applications was carried out in accordance with ethical principles.

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