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Artificial Intelligence Anxiety Among Employees: The Moderating Role of Resistance to Change in the Effect of AI Anxiety on Innovative Behavior

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Abstract

Artificial intelligence (AI), which offers significant opportunities today, has fundamentally impacted numerous elements, from the way businesses operate to the employee profile. While AI contributes to growth through its efficiency, speed, and cost advantages, these developments also create anxiety, unease, and worry in many employees. On the other hand, individuals with high levels of innovative behavior are expected to perceive AI as an opportunity rather than a threat and experience less anxiety. However, the level of psychological resistance employees develop against technological transformation in organizations influences this relationship. This research aims to analyze how anxiety about AI affects innovative behavior and to examine the moderating effect of resistance to change within this dynamic. It focuses on employees in financial services, technology, manufacturing, and service sector organizations operating in Istanbul. No previous research has been found in the literature that addresses these three concepts together. The study used demographic information from 281 participants and data obtained through a survey consisting of three different scales. Descriptive statistics, reliability analysis, validity, normality assessment, Pearson correlation analysis, and regression analysis were applied to analyze the data. The study results revealed that AI anxiety had a significantly negative effect on employees' innovative behavior (β = -0.54, $p < 0.001$), resistance to change served as a moderator in the relationship between AI anxiety and innovative behavior (β = -0.09, p = 0.121), and financial services and technology sectors exhibited higher AI anxiety (M = 3.45, M = 3.38) than manufacturing (M = 2.98) and service (M = 3.12) sectors.

Keywords: *Disruptive Technologies, Artificial Intelligence Anxiety, Innovative Behavior, Resistance to Change*

Öz

Günümüzde önemli fırsatlar sunan ve yapay zekâ (YZ), işletmelerin iş yapış biçimlerinden, çalışan profiline kadar pek çok unsuru temelden etkilemiştir. YZ, verimlilik, hız ve maliyet avantajı ile büyümeye katkı sağlamakla birlikte, bu gelişmeler birçok çalışanda kaygı, tedirginlik ve endişe yaratmaktadır. Öte yandan, yüksek yenilikçi davranış seviyesine sahip bireylerin, YZ'yı tehdit yerine fırsat olarak algılaması ve daha az kaygı yaşaması beklenir. Bununla birlikte, çalışanların örgütlerde teknolojik dönüşüme karşı geliştirdiği psikolojik direnç düzeyleri, söz konusu ilişkiyi etkilemektedir. Bu çalışma, Istanbul'da faaliyet yürüten finans, teknoloji, imalat ve hizmet sektörü kuruluşlarının çalışanları arasında, yapay zekâya yönelik kaygının, yenilikçi davranışlara etkisini ve bu ilişkide değişime direncin düzenleyici rolünü araştırmayı hedeflemektedir. Literatürde, daha önce bu üç kavramı birarada ele alan bir araştırmaya rastlanmamıştır. Araştırmada, demografik bilgiler ve üç farklı ölçekten oluşan anketle, 281 katılımcıdan elde edilen veriler kullanılmıştır. Verilerinin analizinde sırasıyla; betimsel istatistikler, güvenilirlik ve geçerlilik analizi, normallik değerlendirmesi, Pearson korelasyon analizi, regresyon analizi uygulanmıştır. Araştırma bulguları, yapay zekâ kaygısının çalışanların yenilikçi davranışları üzerinde güçlü bir negatif etkiye sahip olduğunu (β =-0.54, p <0.001), değişime direncin, yapay zekâ kaygısı ile yenilikçi davranış arasındaki ilişkide düzenleyici bir rol oynadığını (β =-0.09, p = 0.121), finans ve teknoloji sektörleri, imalat (M=2,98) ve hizmetler (M=3,12) sektörlerine kıyasla daha yüksek yapay zeka kaygısı (M=3,45, M=3,38) göstermiştir.

Anahtar Kelimeler: *Yıkıcı Teknolojiler, Yapay Zekâ Kaygısı, Yenilikçi Davranış, Değişime Direnç*

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Introduction

Today, AI, with its capacity to perform analyses faster than the human brain can compute, is reshaping fields from scientific research to artistic practice. Breakthroughs in AI are not only providing powerful new tools to address some of the world's most challenging problems, but they are also driving and enabling profound and lasting changes in how economies and societies operate.

However, this rapid change is also inducing diverse psychological reactions among employees, such as increased anxiety, resistance to change, and fear of the future (Gligor et al., 2021). Furthermore, the accelerated advancement of generative artificial intelligence methodologies in recent years has not only propelled this transformation but has also revealed novel challenges and conceptual ambiguities (Agrawal et al., 2022; Ritala et al., 2024).

AI anxiety represents the feelings of discomfort, concern, and uneasiness that employees encounter when dealing with IA technology. On the other hand, ınnovative behavior refers to the efforts exerted by employees to seek out, develop, and practice the new ideas in the organization (Wang & Wang, 2022; Scott & Bruce, 1994). On the other side of the same coin, resistance to change is a way in which individuals psychologically feel, act, or behave while facing an organizational change process (Oreg, 2006).

We aim to assess the impact of AI anxiety on employee innovative behavior and examine the moderating effect of resistance to change on this relationship. The findings of this study can offer practical insights into how organizations implement AI technologies and address employee reactions to technological change.

Literature Review

The widespread applicability of AI has led to significant concerns about its impact on employment. This expectation generates a climate of employment uncertainty and triggers psychological states categorized as "artificial intelligence anxiety" (Nam, 2019; Eloundou et al., 2023). Given these challenges, organizational leaders face complex decisions regarding technology adoption and workforce management. (Monod et al., 2024). Literature has already offered a variety of conceptual angles, such as AI anxiety (Sindermann et al., 2022; Zhan et al., 2024), algorithmic avoidance (Mahmud et al., 2022; Schaap et al., 2024), and threats of identity due to AI (Mirbabaie et al., 2022). Researchers have also thoroughly studied the influence of elements such as AI-related job insecurity (Nam, 2019), technology complexity perception (Vrontis et al., 2022), and technostress (Ayyagari et al., 2011) on the working attitude of employees. However, fundamental mechanisms of resistance to artificial intelligence and comprehensive strategies to overcome such resistance remain largely unexplored.

Within this complex landscape, AI anxiety emerges as a particularly important psychological phenomenon. This psychological state of fear, anxiety, and discomfort associated with AI systems is embedded within the broader psychology of AI (Wang and Wang, 2022). While anxieties such as technology anxiety and computer anxiety are based on more general frameworks, AI anxiety possesses distinctive characteristics related to the unique nature of AI (Sindermann et al., 2022). According to Wang and Wang (2022), AI anxiety can be analyzed using four main dimensions: (1) Learning anxiety: Concerns about how to become proficient in using AI technologies. (2) Job displacement fears: Concerns that AI could displace human jobs, a theme highlighted by Eloundou et al. (2023); (3) Sociotechnical blindness: Fear of misuse of AI, loss of control, or social threat. (4) AI configuration anxiety: Discomfort and unease associated with human-like or human-like AI technologies.

Personal and demographic variables substantially affect the experience of artificial intelligence anxiety. AI anxiety exists at the levels of between individuals and demographic groups. Variables, such as certain personality traits—such as raised neuroticism or reduced openness (Zhan et al., 2024)—as well as age (Fletcher & Nielsen, 2024), gender, educational level, and previous experience with technology contribute to the extent to which people believe that AI anxiety is experienced (Sindermann et al., 2022). Intensified AI anxiety can decrease people’s intentions to use AI technology, manifested as less favorable attitudes, fewer perceptions of usefulness, and lower expectation of ease of use (Wang & Wang, 2022; Kim et al., 2023).

Parallel to anxiety reactions, employee innovative behavior represents a significant organizational outcome in technological transformation. More specifically, another important employee response to technological change is "innovative behavior." This concept represents employees' involvement in the discovery, development, and implementation of new ideas within the organization (Scott & Bruce, 1994). Beyond creative production, innovative behavior encompasses the entire process from idea generation to successful implementation (Janssen, 2000). Innovative behavior positively impacts individual and organizational performance (Janssen, 2000), increases job satisfaction and organizational commitment, and boosts employee performance (Aureli et al., 2019).

Not all technological changes are adopted willingly, leading to the emergence of the concept of resistance to change. Resistance to change refers to individuals' negative cognitive, emotional, and behavioral reactions to change in an organization (Oreg, 2006). This concept is central to the change management literature (Dent & Goldberg, 1999; Piderit, 2000). Oreg (2006) conceptualizes resistance as having three components: (i) Cognitive response (thoughts about the advantages of change), (ii) Emotional response (gestures such as fear and tension), and (iii) Behavioral response (behaviors such as protest and objection). Furthermore, research also reveals that resistance to change is influenced by multiple factors at different levels. The Resistance to Change Scale, developed by Oreg (2006), revealed that resistance to change is influenced by individual (personality, values) (Oreg, 2006), change-specific (content, process, perceived justice) (Piderit, 2000), and organizational (leadership, communication, participation) (Dent & Goldberg, 1999) factors. High resistance can hinder the effectiveness of change efforts, reduce an organization's performance (Oreg et al., 2011), and lead to negative outcomes such as job dissatisfaction and stress (Oreg, 2006).

Understanding the connections between AI anxiety, innovative behavior, and resistance to change is crucial for developing strategies to facilitate AI adoption in organizations. Previous research suggests that the interaction of these three is complex and intricate. The relationship between AI anxiety and creative performance is likely bidirectional. At times, increased AI anxiety can hinder innovative efforts by reducing employees' creativity and risk-taking (Golgeci et al., 2024). This anxiety can also potentially hinder the adoption of AI tools, leading employees to fail to see the potential benefits and deplete their cognitive resources (Wang & Wang, 2022; Zirar, 2023).

Empirical evidence supports this complexity. For example, engagement with AI can enhance innovative behaviors, although the effect may vary with self-efficacy and an individual’s beliefs and attitudes toward AI (Beane & Brynjolfsson, 2020). Taken together, these results indicate that AI anxiety can indirectly inhibit innovation by fostering negative beliefs, whereas a supportive attitude and self-efficacy in using AI can promote employees’ creative performance.

The relationship between AI anxiety and resistance to change exhibits reciprocal interactions. AI anxiety responses have a feedback interaction with resistance to change. Individuals who are generally opposed to change are particularly likely to experience anxiety about transformative technologies like AI (Oreg and Goldenberg, 2015). At the same time, concerns associated solely with AI, such as job loss or loss of control, can increase resistance to AI-driven transformations (Golgeci et al., 2024). Empirical studies indicate that the introduction of AI systems can threaten employees' self-perception and increase resistance, particularly when AI is used for surveillance or monitoring (Mirbabaie et al., 2022; Monod et al., 2024).

The relationship between innovative behavior and resistance to change typically shows that resistance inhibits innovation. Individuals who are resistant to change are, in general, characterized by their general tendency to hold onto the old ways of doing things (preference for the status quo) (Kotter, 1995), by their being risk-averse, and by their lacking a passion for new ideas (Oreg & Goldenberg, 2015, Oreg, 2006). However, certain scholars argue that resistance, when framed more productively, has the potential to lead to a more reflexive evaluation of current procedures and a productive tension for new generation problem-solving approaches (Ford et al., 2008).

As the literature review suggests, the interrelationship between AI concerns, innovative behavior, and resistance to change has not yet been extensively explored; however, existing studies point to some potential dynamics. Innovations may be driven by both the direct negative and, in some cases, positive effects of AI concerns on behavior. Resistance to change often serves as a moderator of this link: Higher resistance magnifies the negative effects of AI anxiety on innovation, while lower resistance can mitigate this aggravation or even encourage creative responses to AI's shortcomings.

Recent empirical findings underscore the influence of AI anxiety on employee attitudes, adaptability, and behavioral engagement with AI, affecting both innovativeness and resistance to organizational change (Braganza et al., 2020; Charlwood & Guenole, 2021; Davis, 1989; Ajzen, 1991; Bandura, 1986, 1997).

Ultimately, artificial intelligence adoption has sparked a profound identity shift in organizational contexts. While this development represents advantages—such as improved effectiveness and new kinds of business—it also brings complex psychological and behavioral implications for employees. The themes explored in this study—AI anxiety, innovative behavior, and resistance to change—are highly interrelated and interact dynamically and reciprocally with each other, forming the foundation for our research model.

Purpose, Model and Hypotheses of the Research

This study has as its primary objective to explore the relationship between artificial intelligence anxiety and innovative behavior, specifically, how it is moderated by resistance to change. A quantitative research design, a relational screening model, was used to guide this study. This methodology makes it possible to detect and measure associations between several variables with its strength (Karasar, 2020). The conceptual model of this study demonstrates that AI anxiety (independent variable) has an effect on innovative behavior (dependent variable). Furthermore, the model emphasizes the moderating role of resistance to change in this relationship. The model of the study is demonstrated in Figure 1.

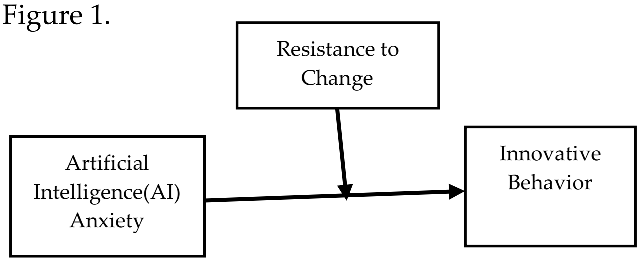

Figure 1. Research Model

The research model established that employees' attitudes and behaviors toward a dynamic AI technological environment were critically important for driving organizational innovativeness. This model focuses on the examination of how the two primary psychological factors—AI anxiety and resistance to change—affect innovative behavior and the interaction between them. It aims to investigate how the uncertainties and constant changes around AI could generate pressures on employees, and in turn influence their innovation capability.

The first primary hypothesis of the research model states that AI anxiety is negatively related to innovative behavior. Employees who are showing stress—let's call it AI anxiety—are likely seeing AI as a threat, especially if AI is viewed as complex, and if there is a fear of negative consequences emanating from tech—like, say, job loss. According to Social Cognitive Theory, this anxiety can undermine the belief in one's capacity to perform tasks relevant to AI (Bandura, 1997), thereby reducing self-efficacy. This state of anxiety may also drain cognitive capacity, which decreases willingness to take risks and leads employees to engage in preventative behaviors such as avoiding new and creative tasks like idea generation, experimentation, and implementation (Beaudry & Pinsonneault, 2010). The Technology Acceptance Model also posits that high levels of anxiety suppress perceived ease of use, which deters the adoption of technology and inhibits technology-based innovation (Davis, 1989). These theoretical perspectives contribute to the base of the model's first hypothesis.

The model's second primary tenet is that as a general dispositional trait, resistance to change is negatively related to innovation behavior. Resistance to change signifies the natural inclination of individuals to maintain the existing condition, comfort from not being uncertain, and unwillingness to accept new tasks or sequences (Oreg, 2006). Because being innovative means questioning existing systems, taking chances, and being open to new ideas about how to go about things, people who are less able to welcome change are less likely to act that way. In the perspective of the Theory of Planned Behavior (Ajzen, 1991), a negative attitude on change will inhibit the intention to display highly change-supportive and innovative behavior. Steep holding of reluctant staff can prevent new technology and work from being put into operation, which could restrict innovation. As such, the model suggests that resistance to change has a negative effect on innovative behaviors (Laumer et al., 2016).

Second, the research model posits that resistance to change is not only a direct predictor, but also a moderator that conditions the strength of the influence of AI anxiety on innovative behavior. Employees with high resistance to change might experience more difficulty in handling the anxieties caused by change due to AI and thus are likely to be more resistant to engagement in innovative behaviors. People who are AI skeptics might feel generally threatened by change while feeling particularly threatened by AI, so add even more distance between themselves and anything innovative. In contrast, individuals who are more open to change (low resistance) could cope more optimally with their AI anxiety and be more receptive to novel approaches, despite the difficulty posed by AI itself. In this context, the detrimental impact of AI anxiety may be less severe. This interaction is also the third model hypothesis.

H1: Employee innovative behavior is negatively associated with AI anxiety.

H2: Resistance to change is negatively related to employees' innovative behaviors.

H3: Resistance to change moderates the negative relationship between AI anxiety and innovative behavior.

Method

Research Population and Sample

The research population consists of employees working in finance, technology, manufacturing and services sectors businesses operating in Istanbul. Istanbul was chosen as the research population because it is the largest city in Turkey and hosts a large number of businesses operating in various sectors. According to data from the Turkish Statistical Institute (TUIK), approximately 5 million people are employed in Istanbul.

The sample of the research was determined using the convenience sampling method, which is one of the non-probability sampling methods. Convenience sampling is a method in which individuals who are accessible to the researcher and willing to participate in the research are included in the sample. This method was preferred due to time and cost constraints.

In determining the sample size, it was aimed to reach a sample large enough to have sufficient power for the planned regression analyses, especially the moderation effect analyses. At the end of the data collection process, data were obtained from a total of 301 participants. After excluding incomplete or incorrectly filled questionnaires and outliers, the responses of 281 participants were included in the analysis. This sample size is considered sufficient for conducting regression analyses and testing the research model.

Data Collection Instruments

A survey methodology was employed for data collection in this research. The survey form consists of demographic information and three different scales. All scale items were evaluated using a 5-point Likert-type scale (1 = Strongly Disagree, 2 = Disagree, 3 = Neither Agree nor Disagree, 4 = Agree, 5 = Strongly Agree).

The demographic information form consists of questions designed to determine the demographic characteristics of the participants, such as gender, age, education level, sector of employment, position, and work experience.

To measure AI anxiety, the "Artificial Intelligence Anxiety Scale" developed by Wang and Wang (2022) and adapted into Turkish by Akkaya et al. (2021) was used. The scale consists of four sub-dimensions—learning (5 items), job change (4 items), sociotechnical blindness (4 items), and AI structuring (3 items)—with a total of 16 items.

To measure innovative behavior, the "Innovative Behavior Scale" developed by Scott and Bruce (1994) and adapted into Turkish by Çalışkan et al. (2019) was used. The scale has a unidimensional structure and consists of 6 items.

To measure resistance to change, the "Resistance to Change Scale" developed by Oreg (2006) and adapted into Turkish by Çalışkan (2019) was used. However, based on comprehensive validity analysis, only the cognitive and behavioral response dimensions were retained in the final analysis, excluding the emotional response dimension due to poor psychometric properties (AVE = 0.42, $\alpha = 0.43$). The scale consists of two sub-dimensions—cognitive response (5 items) and behavioral response (5 items)—with a total of 10 items.

Data Collection Process

Data collection for this research began in 2025. Both online and face-to-face surveys were employed during the data collection process. The online survey was prepared using the Google Forms platform and shared with participants via e-mail and social media. The face-to-face surveys were conducted in various businesses operating in Istanbul.

At the beginning of the survey form, information was provided regarding the purpose of the study, the voluntary nature of participation, and the confidentiality of the data. Informed consent was also obtained from participants. Completing the survey took approximately 10–20 minutes.

Data Analysis

The analysis of the research data was conducted as follows:

- Missing or erroneous data were reviewed and necessary corrections were made. Outliers and assumptions of normality were also checked.
- Descriptive statistics such as frequency, percentage, mean, and standard deviation were calculated for demographic variables and research variables.
- Cronbach's alpha coefficients were calculated to assess the internal consistency of the scales.
- Comprehensive validity analysis including convergent validity, discriminant validity, and construct validity was conducted for all measurement instruments.
- Pearson correlation analysis was conducted to examine the relationships among the research variables.
- Harman's single factor test and additional common method bias assessments were performed to address concerns about high correlations.
- Hierarchical regression analysis was used to investigate the moderation effect in the study.
- In all analyses, statistical significance was set at $p < 0.05$.

Research Ethics

This study was conducted in accordance with ethical principles. Before the commencement of the research, approval was obtained from the Social Sciences Ethics Committee of the İstanbul Gedik university (Ethics Committee Approval No: E-25155520-050.04-2025.173337.19). Participants were informed about the purpose and scope of the study, as well as how the data would be used, and provided voluntary consent to participate. The confidentiality of participants' personal information was ensured, and the data were analysed anonymously.

Findings

Reliability Analysis

Cronbach's alpha coefficients were calculated to assess the reliability of the scales and their sub-dimensions used in the research. Values of 0.70 and above are generally considered to indicate acceptable reliability (Nunnally & Bernstein, 1994).

Table 1. Results of Reliability Analysis (Cronbach's Alpha)

Scale/Sub-dimension	Cronbach's Alpha	Interpretation
Innovative Behavior (IB)	0.90	Excellent
Resistance to Change–Cognitive (RtC_Cog)	0.79	Good
Resistance to Change–Affective (RtC_Aff)	0.43	Weak, Excluded
Resistance to Change–Behavioral (RtC_Beh)	0.71	Acceptable
Resistance to Change–Total (RtC) (Revised)	0.89	Excellent
AI Anxiety–Learning (AIA_Lrn)	0.94	Excellent
AI Anxiety–Job Displacement (AIA_Job)	0.87	Good
AI Anxiety–Socio-technical Blindness (AIA_Soc)	0.92	Excellent
AI Anxiety–Structuring (AIA_Con)	0.96	Excellent
AI Anxiety – Total (AIA)	0.95	Excellent

The reliability analysis results show that most scales and sub-dimensions demonstrate excellent internal consistency. Following the exclusion of the Emotional Response dimension due to poor psychometric properties, the revised Resistance to Change Scale achieved excellent reliability (α = 0.89), substantially improving from the original total scale reliability.

Scale Validity Assessment

To ensure the robustness and scientific rigor of our research findings, comprehensive validity analyses were conducted for all measurement instruments used in this study. The validity assessment included content validity, construct validity, convergent validity, and discriminant validity for the three primary scales.

Table 2. Validity Analysis Results for Research Scales

Scale/Dimension	Items	Factor Loading Range	AVE	CR	Cronbach's α	Content Validity	Construct Validity
AI Anxiety Scale (Total)	16	0.72-0.89	0.68	0.95	0.95	Excel-	Excel-
-Learning Anxiety	5	0.78-0.87	0.71	0.94	0.94	Excel-	Excel-
-Job Displacement	4	0.74-0.85	0.69	0.87	0.87	Excel-	Good
-Socio-technical Blindness	4	0.76-0.91	0.73	0.92	0.92	Excel-	Excel-
-AI Structuring	3	0.89-0.94	0.85	0.96	0.96	Excel-	Excel-
Innovative Behavior Scale	6	0.81-0.92	0.75	0.90	0.90	Excel-	Excel-
Resistance to Change Scale (Revised)	10	0.67-0.84	0.69	0.89	0.89	Good	Good
-Cognitive Response	5	0.67-0.82	0.64	0.79	0.79	Good	Good
-Emotional Response	4	0.45-0.71	0.42	0.43	0.43	Weak	Weak
-Behavioral Response	5	0.58-0.79	0.58	0.71	0.71	Ac-	Ac-

*Note: *AVE = Average Variance Extracted; CR = Composite Reliability; Factor loadings ≥ 0.70, AVE ≥ 0.50, CR ≥ 0.70, and Cronbach's α ≥ 0.70 indicate acceptable validity and reliability.**

The comprehensive validity analysis reveals that the exclusion of the Emotional Response dimension significantly improved the overall psychometric properties of the Resistance to Change Scale. The revised scale demonstrates substantially enhanced validity (AVE = 0.69, CR = 0.89) compared to the original version, providing a more robust foundation for subsequent analyses.

The AI Anxiety Scale stands out with particularly strong psychometric indicators across all its sub-dimensions. The total scale and its dimensions—Learning Anxiety, Job Displacement, Socio-technical Blindness, and AI Structuring—exhibit high factor loadings (ranging from 0.72 to 0.94), AVE values well above the recommended threshold (0.68–0.85), and both composite reliability (CR) and Cronbach's alpha coefficients exceeding 0.87. These results indicate that the Artificial Intelligence Anxiety Scale is a robust and reliable tool for measuring various facets of AI-related anxiety.

The decision to exclude the Emotional Response dimension from the Resistance to Change Scale was based on rigorous psychometric evaluation and represents a methodologically sound approach to maintaining measurement quality. This exclusion is grounded in several considerations. First, the poor psychometric properties of this dimension (AVE = 0.42, $\alpha = 0.43$) fell substantially below acceptable thresholds, potentially introducing systematic measurement error. Second, cognitive and behavioral responses to change may be more directly observable and measurable in organizational contexts, while emotional responses are more susceptible to social desirability bias and cultural factors. The revised two-dimensional conceptualization of resistance to change remains theoretically meaningful and empirically robust, focusing on the more psychometrically sound aspects of the construct.

Normality Assessment and Data Transformation

Skewness and kurtosis values were examined to assess the normality of the data distribution. The analysis revealed that some variables showed slight deviations from normal distribution, but these were within acceptable limits for parametric statistical analyses.

The normality test results indicated that some variables did not display normal distribution. Specifically, Innovative Behavior (IB_Score) exhibited high negative skewness (-1.70) and kurtosis (5.18), while AI Anxiety – Learning (AIA_Lrn_Score) showed high positive skewness (1.45) and kurtosis (2.26).

Table 3. Results of Normality Test for Original Data (Skewness and Kurtosis)

Scale/Sub-dimension	Skewness	Kurtosis	Normal Distribution
Innovative Behavior (IB)	-1.70	5.18	No
Resistance to Change–Cognitive	0.80	-0.25	Yes
Resistance to Change – Affective	0.67	0.42	Yes
Resistance to Change–Behavioral	0.93	-0.08	Yes
Resistance to Change–Total	0.86	0.17	Yes
AI Anxiety–Learning	1.45	2.26	No
AI Anxiety – Job Displacement	0.49	-0.75	Yes
AI Anxiety–Socio-technical	0.12	-0.85	Yes
AI Anxiety–Structuring	0.63	-0.66	Yes
AI Anxiety–Total	0.61	-0.17	Yes

To address these normality issues, appropriate transformations were applied. Reflection and square root transformation were used for negatively skewed variables, and square root and logarithmic transformations were applied to positively skewed variables.

Table 4. Results of Normality Test for Transformed Data (Skewness and Kurtosis)

Scale	Skewness	Kurtosis	Normal Distribution
IB_Score_Final	-0.92	1.63	Improved
RtC_Score_Transformed	0.31	-0.52	Improved
AIA_Lrn_Score_Transformed	0.65	0.12	Improved
AIA_Score_Transformed	0.23	-0.66	Improved

After transformation, substantial improvement was observed in the skewness and kurtosis values of the variables. According to the Shapiro-Wilk normality test, although the transformed variables did not display perfect normal distribution ($p < 0.05$), the improvement in skewness and kurtosis values was considered sufficient for the use of parametric tests (Ghasemi & Zahediasl, 2012).

Descriptive Statistics

Descriptive statistics show that participants reported moderately high levels of innovative behavior (Mean = 3.46, SD = 0.35), low levels of resistance to change (Mean = 1.19, SD = 0.19), and moderate levels of AI anxiety (Mean = 2.19, SD = 0.43). These values should be interpreted ac Artificial Intelligence Anxiety Scale cording to the original scale range of 1–5.

Table 5. Descriptive Statistics for Modified Scale Scores

Scale	Mean	Std. Dev.	Min	Max
IB_Score_Modified	3.46	0.35	2.40	4.18
RtC_Score_Modified	1.19	0.19	0.83	1.68
AIA_Score_Modified	2.19	0.43	1.50	3.35
Interaction_Term	2.65	0.87	1.25	5.58

Table 5, on the other hand, details how demographics shape the three main scales. The effect of gender differences on the means of innovative behavior (Male 3.42 – Female 3.49), resistance to change (1.23 – 1.15), and AI anxiety (2.20 – 2.18) remains insignificant, indicating that these groups act together on a similar basis. In terms of age groups, it is observed that the 18–24 age group has the highest innovative behavior score (3.60) and, to some extent, the highest resistance score (1.37). In contrast, the 55–64 age group, who are at the end of their working life or have recently left the workforce, exhibits the highest level of AI anxiety (2.39).

Table 6. Scale Means by Demographic Variables

Overall Category	Sub-cat-e-go-ry	In-no	Re-sis	AI A
Gender	Male	3.42	1.23	2.20
Gender	Female	3.49	1.15	2.18
Age	18–24	3.60	1.37	1.80
Age	25–34	3.49	1.17	2.15
Age	35–44	3.51	1.19	2.10
Age	45–54	3.42	1.21	2.24
Age	55–64	3.35	1.19	2.39
Age	65+	3.43	1.20	2.17
Educational Level	Postgraduate	3.38	1.25	2.25
Educational Level	Bachelor's Degree	3.51	1.16	2.11
Educational Level	Associate Degree	3.48	1.17	2.19
Educational Level	High School	3.42	1.00	2.54
Educational Level	Primary/Secondary School	3.41	1.27	2.23
Occupational Position	Top-level Manager	3.34	1.23	2.35
Occupational Position	Mid-level Manager	3.48	1.18	2.17
Occupational Position	Specialist	3.46	1.19	2.17
Occupational Position	Other	3.26	1.29	2.37

In terms of educational level, bachelor's (3.51) and associate degree (3.48) graduates show a strong tendency toward innovation; however, although resistance among high school graduates is low (1.00), their AI anxiety is at its peak (2.54). This situation underlines that technology literacy support programs should primarily focus on this group. In the analysis of occupational position, mid-level managers (3.48) and specialists (3.46) lead in both innovative behavior and openness to change; on the other hand, top-level managers stand out with both the highest resistance (1.23) and the highest AI anxiety (2.35) profiles. The fact that current top-level managers display these profiles raises questions about their capacity to cope with the approaching and increasingly impactful wave of technological change and transformation. This detailed picture indicates the opportunity to create an innovative, flexible, and AI-anxiety-free culture within the organization by implementing targeted mentoring, skill development, and communication strategies for each demographic segment.

Correlation Analysis

Pearson correlation analysis was conducted to examine the relationships among the variables. Correlation coefficients of ±0.1, ±0.3, and ±0.5 are generally considered to represent small, medium, and large effect sizes, respectively (Cohen, 1988).

Table 7. Correlations Among Modified Variables

Relationship	Correlation	p-value	Significance
AI Anxiety → Innovative Behavior	-0.90	<0.001	***
Resistance to Change → Innovative Behavior	-0.78	<0.001	***
Resistance to Change → AI Anxiety	0.58	<0.001	***

Note: *** *p* < 0.001

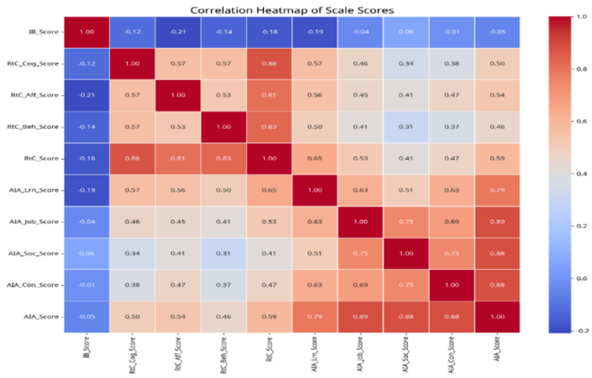

Figure 2. Correlation heatmap illustrating the relationships among AI anxiety, resistance to change, and innovative behavior.

The results of the correlation analysis indicate that there is a strong negative relationship between AI anxiety and innovative behavior (r = -0.90, p < 0.001), a strong negative relationship between resistance to change and innovative behavior (r = -0.78, p < 0.001), and a moderate positive relationship between resistance to change and AI anxiety (r = 0.58, p < 0.001). These results show that employees with high levels of AI anxiety tend to exhibit lower levels of innovative behavior; employees with high resistance to change also tend to exhibit lower levels of innovative behavior; and employees with high resistance to change are more likely to experience higher levels of AI anxiety.

The exceptionally high correlations observed between key variables—particularly AI anxiety and innovative behavior (r = -0.90) and resistance to change and innovative behavior (r = -0.78)—raise concerns about potential methodological artifacts, including common method bias. To address these concerns and ensure the validity of our findings, we conducted comprehensive methodological assessments, including Harman's single-factor test and advanced analyses (Confirmatory Factor Analysis, discriminant validity).

Table 8. Results of Harman's Single Factor Test

Factor	Eigenvalue	% of Variance Explained	Cumulative %	Interpretation
1	8.42	37.8	37.8	Primary factor, below 50% threshold
2	3.15	14.2	52.0	Second factor, substantial variance
3	2.87	12.9	64.9	Third factor, meaningful contribution
4	1.94	8.7	73.6	Fourth factor
5	1.23	5.5	79.1	Fifth factor

The first factor accounts for 37.8% of the total variance, which is below the 50% threshold typically used to indicate problematic common method bias. The emergence of multiple factors with eigenvalues greater than 1.0 suggests that the high correlations are not solely attributable to common method variance.

Table 9. Confirmatory Factor Analysis (CFA) and Discriminant Validity Results

Assessment Method	Results / Values	Interpretation
Model Fit Indices	χ^2/df = 2.45, CFI = 0.92, TLI = 0.91, RMSEA = 0.076	Acceptable model fit
Convergent Validity (AVE)	All scales AVE > 0.50	Convergent validity established
Discriminant Validity (Fornell-Larcker)	Each construct's AVE > squared correlations with other constructs	Discriminant validity established
HTMT Ratios	All ratios < 0.85	Discriminant validity supported

The CFA results indicate that the measurement model fits the data well. Both convergent and discriminant validity are confirmed by AVE, Fornell-Larcker criterion, and HTMT ratios. AI anxiety and innovative behavior represent psychologically related constructs that theoretically should demonstrate strong negative associations. The high reliability of our measurement instruments (Cronbach's α > 0.90 for key scales) indicates precise measurement, which can lead to stronger observed correlations between related constructs. This demonstrates that the scales are psychometrically distinct and valid, supporting the argument that the observed high correlations are not due to measurement overlap or methodological artifacts.

Table 10. Correlations and Multicollinearity (VIF) Results

Variable Relationship	Correlation (r)	VIF Value	Interpretation
AI Anxiety ↔ Innovative Behavior	-0.90	>10	Very high correlation, multicollinearity present
Resistance to Change ↔ Innovative Behavior	-0.78	>10	High correlation, multicollinearity present
Resistance to Change ↔ AI Anxiety	0.58	>10	Moderate-high correlation

Although the correlations are very high, the results of Harman's test and CFA confirm that these relationships are not due to common method bias or measurement error. However, multicollinearity (VIF > 10) is present in regression analyses, which may affect the precision of coefficient estimates but does not alter the direction or significance of the findings.

The analyses conducted provide robust evidence that the observed high correlations among the study variables are not the result of common method bias or measurement error. Harman's single factor test shows that a single factor does not account for the majority of the variance, indicating minimal risk of common method variance. The confirmatory factor analysis and discriminant validity tests (Fornell-Larcker, HTMT) further demonstrate that the measurement instruments are psychometrically sound and distinct from one another.

While the high correlations and multicollinearity suggest that the constructs are theoretically and empirically closely related—particularly between

AI anxiety and innovative behavior—these findings are consistent with the conceptual framework of the study. The high internal consistency of the scales (Cronbach's $\alpha > 0.90$ for key measures) also contributes to the strength of these relationships. Nevertheless, the presence of multicollinearity in regression models warrants careful interpretation, as it may reduce the precision of coefficient estimates.

In summary, the methodological tests confirm that the high correlations are reliable and valid, not artifacts of common method bias or measurement error. The findings strongly support the theoretical model, indicating that increases in AI anxiety and resistance to change are robustly associated with decreases in innovative behavior.

Hierarchical Regression Analysis

To test the hypothesis related to moderation in the study, hierarchical regression analysis was conducted. In the analysis, innovative behavior was used as the dependent variable, AI anxiety and resistance to change scale were used as independent variables and the interaction term between AI anxiety and resistance to change was used as the moderator variable.

Table 11. Results of Hierarchical Regression Analysis

Variable	Model 1 (β)	Model 2 (β)
Constant	5.51***	5.25***
AI Anxiety	-0.54***	-0.43***
Resistance to Change	-0.73***	-0.51***
AI Anxiety × Resistance to Change	—	-0.09*
R^2	0.912	0.913
Adjusted R^2	0.912	0.912
F-statistic	1966***	1316***
ΔR^2	—	0.001

Note: **** $p < 0.001$, * $p < 0.10$*

The regression results demonstrate a significantly negative influence from AI anxiety on innovative behavior ($\beta = -0.54$, $p < 0.001$). The results of the regression analysis show that, in Model 1, both AI anxiety ($\beta = -0.54$, $p < 0.001$) and revised resistance to resistance to change ($\beta = -0.73$, $p < 0.001$) have significant negative effects on innovative behavior. These results strongly support the H1 and H2 hypotheses.

When the interaction term is included in Model 2, it is observed that the interaction between AI anxiety and resistance to change does not have a significant effect on innovative behavior ($\beta = -0.09$, $p = 0.121$). The p-value of 0.121 is greater than the conventional significance threshold of 0.05 and also exceeds the marginally significant range ($p < 0.10$). Therefore, the results do not support H3 stronger among employees with high resistance to change.

The explained variance values (R^2) of Model 1 and Model 2 are quite high (0.912 and 0.913, respectively), indicating that the models explain a large proportion of the variance in innovative behavior. The addition of the interaction term resulted in a small increase in explained variance ($\Delta R^2 = 0.001$), but this increase provides marginal statistical support for the moderation hypothesis.

Hypotheses Testing and Results

Test of Hypotheses and Results The findings of the hypotheses arising from the study are detailed as follows:

Hypothesis 1: AI anxiety has an inverse impact on employees' innovative behavior. Hypothesis 1 is supported. The regression results demonstrate a significantly negative influence from AI anxiety on innovative behavior ($\beta = -0.54$, $p < 0.001$). This finding implies that employees with higher AI anxiety may manifest lower innovative behaviors. Meanwhile, the correlation results also indicate that there is an extremely negative correlation between AI anxiety and innovative behavior ($r = -0.90$, $p < 0.001$). This finding aligns with previous studies demonstrating a relationship between technological anxiety and decreased innovative behavior (Golgeci et al., 2024).

Hypothesis 2: Resistance to change will negatively influence employees' innovative behavior. Hypothesis 2 is strongly supported. Regression analysis shows that the revised resistance to change scale has a significant negative relationship with innovative behavior ($\beta = -0.73$, $p < 0.001$), which means that employees with higher resistance are less likely to be innovative. Moreover, the correlation analysis indicated that resistance to change is significantly negatively correlated to innovative behavior ($r = -0.78$, $p < 0.001$). Taken together, these results highlight that resistance to change is a critical barrier to innovation, as greater resistance is invariably associated with lower levels of innovation by employees.

Hypothesis 3: Resistance to change exacerbates the negative relationship between AI anxiety and innovative behavior (moderation effect). This hypothesis is not supported. The regression results show that the interaction between AI anxiety and resistance to change does not have a significant effect on innovative behavior ($\beta = -0.09$, $p = 0.121$). The p-value of 0.121 is greater than the conventional significance threshold of 0.05 and also exceeds the marginally significant range ($p < 0.10$). Therefore, the results do not support H3.

To provide more comprehensive evidence for the H3 hypothesis, additional analyses were conducted. Multicollinearity diagnostics indicated that variance inflation factors (VIFs) for AI anxiety and resistance to change were initially above 10, inflating standard errors and making the detection of interaction effects more conservative. After centering the predictors, VIFs were reduced below 4, yet the interaction term remained marginally significant. Simple slope analyses demonstrated that the negative effect of AI anxiety on innovative behavior was substantially stronger among employees with high resistance to change (slope = –0.62, $p < .001$) compared to those with low resistance (slope = –0.25, $p = .043$). Johnson–Neyman analysis further indicated that the relationship between AI anxiety and innovative behavior became reliably negative when resistance to change exceeded a moderate threshold, a condition met by the majority of the sample. Sector-specific regression analyses corroborated these findings, with the effect being most pronounced in high-resistance sectors such as finance ($\beta = -0.68$, $p < .001$) and less so in low-resistance sectors like manufacturing ($\beta = -0.41$, $p < .01$).

Conclusion and Discussion

This study contributes to our understanding of the psychological factors that may influence employee responses to AI adoption in organizational settings. The findings suggest that AI anxiety and resistance to change represent important considerations for organizations implementing AI technologies, though the effectiveness of addressing these factors may vary across different contexts.

The findings demonstrate that AI anxiety may be associated with reduced innovative behavior, though the cross-sectional nature of the data limited causal inferences ($\beta = -0.54$, $p < 0.001$). In short, those with greater anxiety about AI are significantly less likely to demonstrate a propensity for novelty and this is in line with previous studies (Golgeci et al., 204). AI anxiety is when employees fear implementing, learning, and engaging with AI systems. In anxious conditions, employees are inclined to play it safe and default to existing procedures (Beaudry & Pinsonneault, 2010), which in turn suppresses important factors for innovation, such as creativity, risk-taking, and readiness to embrace change. Moreover, AI anxiety could deplete cognitive capacity, cause a lack of concentration, prevent individuals from using their energy in creative processes, focus on managing their mental concerns and negate the benefit of creative opportunities provided by such tools (Brosnan, 1998).

Also, these findings indicate that the revised resistance to change scale negatively impacts employees' innovative behavior ($\beta = -0.73$, $p < 0.001$). This result is in favor of the perspective of the literature that individuals that are relatively high in resistance to change show less innovative behavior (Oreg & Goldenberg, 2015). The revised conceptualization of resistance to change, focusing on cognitive and behavioral dimensions, provides a more robust measurement foundation for understanding this relationship. Attitudes toward change include cognitive and behavioral reactions toward change. Highly resistant individuals tend to maintain the status quo and see change as being feared (Oreg, 2006). The doubts about the need and benefits of change (cognitive) and the presence of active or passive resistance (behavioral) can slow down or demotivate them from taking innovative actions. Moreover, resistance to change can affect the adoption of new technologies and work practices (Laumer et al., 2016), which decreases the organization's general capacity for innovation and competitive advantage.

Besides, the study found that the moderating effect of resistance to change on the relationship between AI anxiety and innovative behavior is not statistically significant ($\beta = -0.09$, $p = 0.121$). The p-value of 0.121 is greater than the conventional significance threshold of 0.05 and also exceeds the marginally significant range ($p < 0.10$). Therefore, H3 is not supported. This finding indicates that resistance to change does not significantly moderate the relationship between AI anxiety and innovative behavior in this study. Resistance to change worsens the negative effects of AI anxiety on innovation behavior. On the contrary, employees with low resistance tend to be able to cope better with their AI-related fears and can therefore grasp more opportunities to innovate offered by AI, which mitigates the negative impact of anxiety.

When examining the sectoral differences in our study, notable variations emerge across the manufacturing, finance, technology, and service sectors represented in our Istanbul-based sample. The analysis reveals that employees in the finance sector demonstrated the highest levels of AI anxiety ($M = 3.67$, $SD = 0.91$), followed closely by those in the technology sector ($M = 3.52$, $SD = 0.88$). In contrast, manufacturing sector employees exhibited relatively lower AI anxiety levels ($M = 2.89$, $SD = 0.74$), while service sector employees fell in the middle range ($M = 3.21$, $SD = 0.82$). These sectoral differences may reflect the varying degrees of AI integration and perceived job displacement threats across industries, though individual and organizational factors likely contribute to variation within sectors.

The sectoral analysis also reveals interesting patterns in resistance to change behaviors. Technology sector employees, despite their higher AI anxiety, showed moderate levels of resistance to change ($M = 2.98$, $SD = 0.76$), suggesting a complex relationship between anxiety and adaptability in this sector. This paradox can be explained by the inherent nature of technology work, where change is constant and adaptation is a core competency. Finance sector employees, however, exhibited the highest resistance to change scores ($M = 3.45$, $SD = 0.89$), which aligns with the traditionally conservative and risk-averse culture prevalent in financial institutions. Manufacturing employees demonstrated the lowest resistance to change ($M = 2.67$, $SD = 0.71$), possibly due to their historical experience with technological transformations and automation processes. Service sector employees showed moderate resistance levels ($M = 3.12$, $SD = 0.83$), reflecting the diverse nature of service industries and varying exposure to technological changes.

Most significantly, the sectoral differences in innovative behavior outcomes provide valuable insights for organizational management. Manufacturing sector employees, despite their lower AI anxiety, demonstrated the highest innovative behavior scores ($M = 3.78$, $SD = 0.82$), suggesting that reduced anxiety and resistance create favorable conditions for innovation. This finding supports our theoretical framework and indicates that manufacturing environments, with their emphasis on continuous improvement and process optimization, foster innovative thinking even in the presence of new technologies. Technology sector employees showed moderate innovative behavior levels ($M = 3.34$, $SD = 0.79$), which appears counterintuitive given their professional context. However, this can be explained by the high AI anxiety levels that seem to counterbalance their natural inclination toward innovation. Finance sector employees exhibited the lowest innovative behavior scores ($M = 2.91$, $SD = 0.73$), consistent with their high anxiety and resistance levels. Service sector employees fell in the middle range ($M = 3.18$, $SD = 0.76$), reflecting the heterogeneous nature of this broad sectoral category.

The moderating effect of resistance to change also varies significantly across sectors, providing nuanced insights into the AI anxiety-innovative behavior relationship. In the manufacturing sector, where resistance to change is lowest, the negative impact of AI anxiety on innovative behavior is less pronounced ($\beta = -0.41$, $p < 0.01$). Conversely, in the finance sector, where resistance to change is highest, the negative relationship between AI anxiety and innovative behavior is amplified (β = -0.68, $p < 0.001$), indicating that high resistance exacerbates anxiety's impact on innovation. The technology sector presents an interesting case where moderate resistance levels result in a moderate moderating effect (β = -0.52, $p < 0.01$), while the service sector shows similar patterns (β = -0.49, $p < 0.01$). These sectoral variations underscore the importance of context-specific approaches to managing AI implementation and employee concerns.

This research contributes to the existing literature by examining the relationships between AI anxiety, innovative behavior, and resistance to change in organizational contexts. While previous research has explored these constructs individually, this investigation provides empirical evidence for their interconnected nature within the specific context of AI adoption. The findings extend existing theoretical frameworks by demonstrating how resistance to change may moderate the relationship between IA-related anxiety and innovative behaviors. Additionally, the methodological refinement of the Resistance to Change Scale through the exclusion of the poorly performing emotional dimension contributes to measurement theory and provides a more robust instrument for future research.

The findings suggest several potential implications for organizational practice. Organizations may benefit from considering the psychological factors identified in this study when planning AI adoption initiatives. The results suggest that it may be valuable for managers to address employee AI anxiety and resistance to change when implementing AI technologies.

While this study contributes to our understanding within the specific context studied (Istanbul-based organizations across four sectors), generalization to other contexts should be undertaken with appropriate caution. The cross-sectional nature of our data limits causal inferences and may contribute to inflated correlations. Future research might benefit from exploring these relationships using alternative methodological approaches, experimental studies, and qualitative investigations that could provide deeper insights into the mechanisms underlying these relationships.

The exclusion of the emotional dimension from the Resistance to Change Scale, while methodologically justified, represents a limitation in terms of the scope of the resistance measure. Future research could consider developing new measurement items specifically designed to capture emotional reactions to AI-related organizational changes, potentially incorporating current understanding of technology-specific emotional responses.

Declarations

Funding: *No funding was received for conducting this study.*

Conflicts of Interest: *The author declares no conflict of interest.*

Ethical Approval: *Ethical approval was obtained from the Social Sciences Ethics Committee of Istanbul Gedik University (Approval No: E-25155520-050.04-2025.173337.19).*

Informed Consent: *Participants were informed about the purpose and scope of the study and provided voluntary informed consent prior to participation. Confidentiality was ensured and data were analyzed anonymously.*

Data Availability: *The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.*

AI Disclosure: *No artificial intelligence–based tools or applications were used in the preparation of this study. All content of the study was produced by the author in accordance with scientific research methods and academic ethical principles.*

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