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The mediating role of individual innovativeness in the relationship between career engagement and artificial intelligence anxiety

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Abstract

This study investigates the mediating role of individual innovativeness in the relationship between career engagement and artificial intelligence (AI) anxiety among university students. Using data from 277 univeristy students, the study employed two-stage structural equation modeling and conducted mediation analysis. Model fit was assessed through chi-square difference tests and comparative fit indices (AIC, ECVI), with the significance of mediation evaluated via bootstrap analysis. Results indicate that while career engagement significantly predicts individual innovativeness, it does not directly predict AI anxiety. However, individual innovativeness significantly predicts AI anxiety and mediates the relationship between career engagement and AI anxiety. These findings highlight the theoretical relevance of individual innovativeness as a psychological mechanism linking proactive career behaviors to emotional responses to emerging technologies. Practically, the study underscore the importance of fostering both career engagement and innovativeness in higher education settings to help students navigate technological uncertainty and reduce AI-related anxieties.

Keywords Artificial intelligence anxiety · Career engagement · Individual innovativeness

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1 Introduction

In recent years, artificial intelligence (AI) has influenced nearly every aspect of society, influencing the economy, politics, science, and education (Chen et al., 2020; Gansser & Reich, 2021; Luan et al., 2020; Makridakis, 2017). AI usually considered as a new revolution, contributing to significant advancements across various domains (Gansser & Reich, 2021). Public opinion on AI is varied, with some individuals rejecting it entirely, others fully embracing its potential, and many falling somewhere in between. Given these complexities in people's views, understanding attitudes toward AI has become increasingly important. Among the emerging concerns is AI anxiety, a psychological response characterized by unease, apprehension, or fear related to the development and integration of AI technologies (Johnson & Verdicchio, 2017). As AI continues to evolve and permeate daily life, exploring the factors contributing to AI anxiety is critical for fostering more informed, balanced, and adaptive engagements with technology, especially in higher education.

In framing this study, it is important to note that AI anxiety can be viewed as a specific expression of a broader category of technology-related anxieties. Earlier constructs such as computer anxiety (Brosnan, 1998), technology anxiety (Meuter et al., 2003), and technostress (Tarafdar et al., 2007) have been used to explain individuals' psychological responses to digital technologies. These constructs are conceptually relevant in that they describe aversive emotional reactions to learning, adopting, or interacting with new technology. Within this context of technology anxiety, which is a well-documented psychological barrier to technology acceptance, emerges as a crucial concept. This issue has become increasingly salient within higher education, where digital transformation is reshaping pedagogical practices, learning environments, and the expectations placed on both students and faculty (Bond et al., 2020; Selwyn, 2021). The integration of AI into educational systems, ranging from intelligent tutoring systems and automated grading tools to AI-driven career guidance platforms, has introduced new sources of uncertainty and concern (Zawacki-Richter et al., 2019).

In higher education, AI anxiety is emerging not only as a response to academic uncertainty but also as a reflection of students' concerns about their future career trajectories. As AI technologies increasingly influence hiring practices, automate professional tasks, and reshape required competencies across sectors (Brynjolfsson & McAfee, 2014), students are compelled to question their relevance, preparedness, and employability in an evolving labor market. This anxiety may be especially pronounced among students in structured professional programs where expectations for future roles are well defined and thus more visibly affected by AI-driven transformation (Zawacki-Richter et al., 2019). Concerns about being replaced by algorithms, facing unpredictable career demands, or lacking technological adaptability can undermine confidence in their vocational futures (Wang & Wang, 2019). In this context, higher education institutions are no longer simply providers of disciplinary knowledge; they are becoming critical environments for fostering adaptability, digital literacy, and proactive career behaviors that equip students to navigate AI-mediated futures. Understanding AI anxiety, therefore, requires a dual lens, attending to both academic and career-related pressures, and underscores the need to explore how

psychological resources such as career engagement and individual innovativeness may serve as buffers against the disruptive emotional effects of technological change.

In addition, recent studies show that AI anxiety manifests differently across populations. For example, professionals often express anxiety concerning job security, ethical transparency, and autonomy loss (Zhang & Dafoe, 2019), while university students may report anxiety associated with learning AI systems, being evaluated by automated tools, or fears about employability (Wang & Wang, 2019). These differing expressions of anxiety reflect context-specific concerns. By focusing on university students, a population navigating both academic demands and early-stage career development, this study explores how career-related dispositions and technological openness interact to shape their affective responses to AI.

1.1 Theoretical framework

This study draws on Career Construction Theory (CCT) and the Technology Acceptance Model (TAM) to provide a comprehensive lens for examining the psychological and perceptual processes underlying students' reactions to AI in the context of career development. CCT emphasizes the importance of psychological adaptability, conceptualized through behaviors such as career engagement and personal resources like individual innovativeness, in navigating career-related uncertainty (Savickas, 2005; Savickas & Porfeli, 2012). In this framework, individual innovativeness reflects an adaptive orientation toward change, a core component of career adaptability, that enables individuals to proactively manage vocational transitions driven by technological disruption. TAM, on the other hand, focuses on how individuals' perceptions, such as perceived usefulness, ease of use, and perceived threat, shape emotional and behavioral responses to new technologies (Agarwal & Prasad, 1998; Davis, 1989). From this perspective, AI anxiety can be interpreted as a form of perception-based resistance to innovation, often triggered when emerging technologies are viewed as complex, uncontrollable, or misaligned with one's capabilities or goals.

By integrating CCT and TAM, the current framework positions individual innovativeness as a key mechanism linking career adaptability (CCT) to perceived technological threat (TAM). In TAM, AI anxiety may arise when individuals perceive AI technologies as complex, uncontrollable, or threatening, reflecting low perceived ease of use and low perceived usefulness. These perceptions can be influenced by personality traits such as individual innovativeness, which increase the likelihood of seeing AI as beneficial and manageable, thereby reducing anxiety. More innovative individuals are more likely to perceive emerging technologies as manageable and beneficial, thus experiencing less anxiety. By combining these perspectives, the current study positions career engagement as a contextual and behavioral predictor, individual innovativeness as both a personal and psychological resource, and AI anxiety as a technological emotional outcome.

1.2 AI anxiety and individual innovations

Research suggests that anxiety in general can hinder creativity and innovation by encouraging risk averse behavior and reducing the cognitive flexibility necessary for

creative thinking (Amabile, 1996; Anderson et al., 2014). This anxiety, particularly when it relates to AI, can further inhibit individuals' willingness to engage with new technologies or explore innovative approaches involving AI tools. Additionally, AI anxiety can negatively impact the psychological safety needed to foster innovation (Wang & Wang, 2019). Psychological safety refers to the belief that one can take risks without fear of negative consequences and is a critical component of environments that support creativity and innovation (Edmondson, 1999). When individuals feel threatened by AI, whether due to fear of invalidation, ethical concerns, or insufficient understanding, they may be less likely to experiment with new ideas or propose innovative solutions. This can hinder the overall innovation process (West et al., 2003).

Innovativeness can be conceptualized as the degree to which an individual adopts innovations more quickly than other members of their community (Rogers & Shoemaker, 1971). Individual innovativeness is generally considered a stable trait or disposition that influences the tendency for a person to respond more positively to new ideas or technologies (Yi et al., 2006). In the context of technology, it can also be viewed as a form of innovation; some individuals tend to adopt information technology innovations earlier than others (Agarwal & Prasad, 1998). Technological innovativeness refers to an individual's tendency to embrace and experiment with emerging technologies (Agarwal & Prasad, 1998), which may shape how they interpret, react to, and cope with the presence of AI in educational and career contexts. Thus, in this study, we focus on individual innovativeness primarily as a proxy for students' openness to and engagement with technological change, particularly AI systems.

Researchers have started to investigate the relationships between AI anxiety and individual innovation, seeking strategies for mitigating AI anxiety to promote individual innovation (Gansser & Reich, 2021; Kaya et al., 2022; Northeastern University, 2018). One effective approach identified is providing targeted training and education about AI, which can reduce anxiety by increasing familiarity and perceived control over the technology (Zhang & Dafoe, 2019). Furthermore, creating an organizational culture that emphasizes the collaborative and augmentative nature of AI, rather than framing it as a replacement for human workers, can help alleviate fears and encourage more innovative uses of AI (Dwivedi et al., 2021).

1.3 AI anxiety and career engagement

As defined by Hirschi et al. (2014), career engagement refers to an individual's active participation in a range of career behaviors focused on advancing their professional development, emphasizing concrete actions rather than attitudes or self-management strategies. Over the past few decades, digital technologies have driven rapid organizational and societal change and have impacted the rapidly changing professional landscape (Vial, 2019). The role of career engagement has become even more critical as AI increasingly impacts how careers are managed and developed. The integration of AI across a range of sectors is not only reshaping job roles, but also requiring individuals to be proactively engaged in their career development to remain competitive and adaptable in the face of these technological advances (Morandini et al., 2023). Frey and Osborne (2017) estimate that 47% of jobs in the UK are at risk of

automation through AI, advanced robotics, or algorithms powered by big data. However, technological advances may not only lead to job losses, but also the creation of new jobs. Automation and emerging technologies have the potential to stimulate economic growth and create demand for new roles (Spencer, 2018).

Career engagement is defined as an individual's active participation and investment in their career development and advancement (Hirschi et al., 2014) and may be influenced by the presence of AI anxiety. As individuals navigate an increasingly AI-driven professional landscape, those experiencing AI-related anxiety may reduce their ability to engage in proactive career behaviors. This anxiety can create barriers to adopting new technologies and undermine commitment to career advancement (Erebak & Turgut, 2021; Synard & Gazzola, 2018). Research suggests that anxiety can reduce an individual's commitment to their career by creating feelings of insecurity and decreasing motivation (Erebak & Turgut, 2021; Greenhalgh & Rosenblatt, 2010). This anxiety, particularly when related to AI, can increase concerns about job loss, skill obsolescence, and the changing nature of work (Brougham & Haar, 2018; Frey & Osborne, 2017). For example, employees who fear that AI will render their skills useless may shy away from career development (Brougham & Haar, 2018; Jarrahi, 2018). Consequently, AI anxiety may also undermine self-efficacy, a key driver of career engagement, the belief in one's ability to achieve career-related goals (Bandura, 1997). Individuals with AI anxiety may doubt their ability to adapt to new technologies or remain competitive in an AI-focused workplace, which reduces engagement and leads to reluctance to pursue advancement opportunities (Brougham & Haar, 2018). This disengagement not only hinders individual career growth but can also negatively impact organizational productivity and innovation (Dwivedi et al., 2021; Park et al., 2022). Thus, understanding the connection between AI anxiety and career engagement is important for both individuals and organizations looking to thrive in an AI-driven world. By addressing AI anxiety, organizations can increase employee engagement and keep employees motivated and invested in their careers in this evolving technology world (Brougham & Haar, 2018; Dwivedi et al., 2021).

1.4 Career engagement and individual innovations

Career engagement, which involves proactive behaviors where individuals actively manage and develop their careers, is closely linked to individual innovation (Crant, 2000; Parker et al., 2006). Proactive career behavior, a broad term describing various actions taken to advance one's career, is integral to career engagement (Segarra-Ciprés et al., 2019). One aspect of career engagement is exhibiting proactive career behaviors, which are essential for fostering innovation (Hirschi et al., 2014; Segarra-Ciprés et al., 2019).

Individual innovation, defined as the implementation of original ideas, processes, products, or procedures (Anderson et al., 2014; West & Farr, 1990), requires proactive behaviors. By their nature, proactive behaviors are change-oriented and future-focused. Therefore, individuals who engage in proactive career behaviors are likely to pursue innovations related to their careers, explore development opportunities, and seize learning prospects that support their career growth (Bateman & Crant, 1993). Innovative individuals adapt to changes, solve complex problems, and achieve inno-

vations (Harari et al., 2018). Researchers agree that proactive personality traits benefit innovative behavior (Rodrigues & Rebelo, 2019).

When individuals are fully engaged in their careers, they invest effort in exploring new ideas, experimenting with different approaches, and taking calculated risks, all of which are essential for innovation (Kahn, 1990). Additionally, career engagement often correlates with a strong sense of purpose and alignment with organizational goals, further encouraging innovative behavior (Janssen, 2000; Rodrigues & Rebelo, 2019). Employees who perceive a clear connection between their work and their broader career aspirations are more likely to pursue opportunities for innovation, viewing them as pathways to career advancement and personal growth (Hall, 2004; Shalley et al., 2017). High levels of engagement and proactive career behavior drive innovation, while opportunities for innovation can, in turn, reinforce career engagement by making work more fulfilling and meaningful (Amabile, 1996; Shalley et al., 2017).

1.5 Purpose of the study

The use of career engagement as a construct in this study is particularly relevant for university students, who are generally situated in the discovery and exploration phases of career development (Super, 1980). During this formative stage, students begin to actively engage in shaping their vocational identity, making decisions that inform their future professional pathways (Arnett, 2000). Although their careers may not be fully established, the psychological processes involved in proactive career planning, such as goal setting, skill acquisition, and seeking career-relevant experiences, are already in operation. Hirschi et al. (2014) emphasize that career engagement reflects not employment status, but rather the degree to which individuals take proactive steps to advance their careers, which is observable even in early adulthood. For university students, career engagement is essential for transitioning from school to work (Sou et al., 2022). In addition, individuals with high career engagement have high career satisfaction, career decision making self-efficacy, confidence in future outcomes, and the probability of finding a job after graduation (Chan, 2017; Hirschi et al., 2014; Kim et al., 2014; Sou et al., 2022). For these reasons, it is essential to investigate university students'career engagement and the associated variables.

When university students show career engagement, they enter the labor market better equipped in addition to their academic success (Blau, 1985). However, the transformation created by AI technologies in the business world changes students'career plans and increases uncertainty in some professions (Frey & Osborne, 2017). Individual innovation is the capacity of an individual to adopt and implement new ideas. University students'innovation facilitates their adaptation to the changing business world (Rogers, 2003). Innovative individuals may take advantage of the opportunities offered by AI by adapting to technological changes faster. However, this transformation may be perceived as a threat for non-innovative individuals. AI anxiety can cause individuals to feel uncertain about the future of their profession. Especially the automation of routine and repetitive tasks increases anxiety in some student groups (Acemoglu & Restrepo, 2020). This anxiety may cause students to change their career orientation or move towards more competitive fields. However, some

studies show that positive attitudes toward AI strengthen their careers by acquiring new skills (Brougham & Haar, 2018).

Understanding how students navigate AI-related challenges requires examining the interplay between career engagement, individual innovativeness, and AI anxiety. Career engagement reflects students' proactive approach to future planning, while innovativeness indicates their openness to technological change. AI anxiety captures their emotional response to emerging technologies. This study investigates whether individual innovativeness mediates the relationship between career engagement and AI anxiety. This interplay becomes especially significant in higher education, where students are not only acquiring disciplinary knowledge but also preparing for lifelong career development. As AI tools become integrated into learning environments, decision-making, and workplace practices, students must cultivate both technological fluency and psychological adaptability. Institutions of higher education must therefore support students not only in developing digital competencies, but also in building resilience, confidence, and future-oriented thinking. Investigating how proactive career behaviors and individual dispositions influence AI-related anxiety offers meaningful insights for designing interventions, support systems, and curricula that prepare students for AI-enhanced futures.

In sum, examining the links among career engagement, individual innovativeness, and AI anxiety offers both theoretical and practical contributions. From a theoretical standpoint, this study contributes to career development and technology acceptance literatures by highlighting the mediating role of psychological traits in shaping technology-related emotional responses. From a practical perspective, the findings can inform how educators and institutions help students build the adaptive capacities needed to navigate complex, technology-driven career environments. Therefore, the aim of this study is to examine the mediating role of individual innovativeness in the relationship between career engagement and AI anxiety. The study aims to contribute to the existing literature by testing the following hypotheses (see Fig. 1):

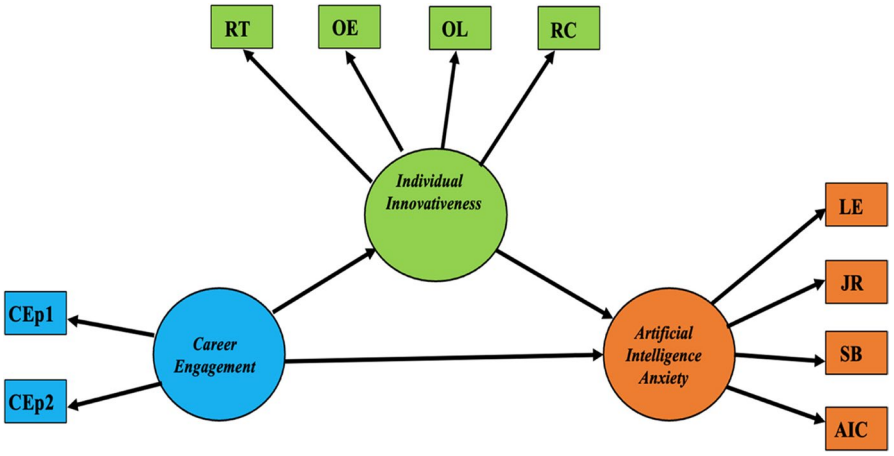

Fig. 1 Hypothetical structural model. Note. CEp1, CEp2= Parcels of Career Engagement, RT: Risk-Taking, OE: Openness to Experience, OL: Opinion-Leading, RC: Resistance to Change, LE: Learning, JR: Job Replacement, SB: Sociotechnical Blindness, AIC: Artificial Intelligence Configuration

H[1]: Career Engagement is a significant predictor of Individual Innovativeness.

H[2]: Individual Innovativeness is a significant predictor of Artificial Intelligence Anxiety.

H[3]: Career Engagement is a significant predictor of Artificial Intelligence Anxiety.

H[4]: The mediating effect of Individual Innovativeness on the relationship between Career Engagement and Artificial Intelligence Anxiety is significant.

2 Method

2.1 Participants and procedure

Participants were recruited using a convenience sampling method from undergraduate courses in education, health sciences, and psychology at a public university in Turkey. Data were collected via an online survey platform and distributed through course instructors and universities Learning Menagement Systems (LMS). Participation was voluntary, and informed consent was obtained electronically before survey completion. A total of 277 students participated in the study. The sample included 216 female (78%) and 61 male (22%) participants. In addition, 142 (51.3%) of these students were enrolled in health-related fields, 97 (35%), of them enrolled in teaching-related programs (e.g., pre-service teacher education), and 38 (13.7%) of them were enrolled psychology-related programs. Notably, the majority of participants in this study were enrolled in education and health sciences programs, fields that are characterized by relatively well-defined professional trajectories.

2.2 Measurement tools

2.2.1 Career Engagement Scale (CES)

CES was developed by Hirschi et al. (2014), and its adaptation into Turkish, validity, and reliability analyses was conducted by Korkmaz et al. (2020). CES has nine items and a unidimensional structure. Since the CES has a unidimensional design, parceling was performed based on the item-total correlation (Alhija & Wisenbaker, 2006). In this context, two virtual factors were assigned for the CES. The results of confirmatory factor analysis conducted to test construct validity revealed acceptable goodness of fit values ($\chi 2 = 118.117$, df = 24, RMSEA =.09, SRMR =.06, CFI =.95 and TLI =.93) (Korkmaz et al., 2020). The Cronbach Alpha reliability coefficient of the CES was determined as.88 (Korkmaz et al., 2020). This study determined the Cronbach Alpha reliability coefficient of the entire CES to be.89.

2.3 Individual Innovativeness Scale (IIS)

IIS was developed by Hurt et al. (1977). Its adaptation into Turkish and psychometric properties was conducted by Kılıçer and Odabaşı (2010). IIS contains twenty items and four dimensions. These dimensions are risk-taking, openness to experience, opinion-leading, and resistance to change. Exploratory factor analysis was con-

ducted for construct validity. According to the study's findings, the eigenvalue of IIS was more significant than 1.0, and the total explained variance was 52.52% (Kılıçer & Odabaşı, 2010). The Cronbach Alpha reliability coefficient of the whole IIS was.82 (Kılıçer & Odabaşı, 2010). This study calculated the Cronbach Alpha reliability coefficient of the entire IIS as.70.

2.3.1 Artificial Intelligence Anxiety Scale (AIAS)

AIAS was developed by Wang and Wang (2019), and its adaptation into Turkish and psychometric studies was conducted by Akkaya et al. (2021). The AIAS has sixteen items and four dimensions. These dimensions are learning, job replacement, sociotechnical blindness, and AI configuration. Confirmatory factor analysis was applied for construct validity. As a result of confirmatory factor analysis, acceptable goodness of fit values ($\chi 2/df$=2.627, RMSEA=.078, RFI=.906, TLI=.940, CFI=.950 and IFI=.951) were obtained (Akkaya et al., 2021). The Cronbach Alpha reliability coefficient of the entire AIAS was found to be.93 (Akkaya et al., 2021). In this study, the Cronbach Alpha reliability coefficient of the AIAS as a whole was found to be.92.

2.4 Data analysis

This study's preliminary analyses (outliers, normality, and multicollinearity) were first evaluated (Kline, 2019). After the preliminary analysis assumptions were examined, the data were analyzed with the two-stage structural equation modeling technique. In other words, a measurement model test was conducted in the first stage. When this measurement model was compatible with the data, the structural model test was performed in the second stage (Anderson & Gerbing, 1988). The goodness of fit values such as [$\chi 2/df$, RMSEA, AGFI, GFI, CFI, and NFI] were used to interpret these models (Schermelleh-Engel et al., 2003).

Mediation analysis was also conducted. At this point, which model (partial or full mediation) is the best model is decided by using the chi-square difference test and comparison fit indices (AIC and ECVI). In addition, whether the mediating effect of individual innovativeness is significant or not was evaluated by bootstrap analysis (Hayes, 2017). For this, 1000 resampling was performed, and lower and upper-bound confidence intervals were determined. The fact that these confidence intervals do not contain zero indicates that this mediation effect is significant (Shrout & Bolger, 2002). Finally, Maximum Likelihood was used as the estimation method.

3 Results

3.1 Preliminary analysis

In this study, a preliminary analysis was first evaluated. In this context, 3 data were found to be outliers and were removed from the data set. Then, the normality assumption was tested by looking at the kurtosis and skewness values. The kurtosis values of this study were found to vary between -.98 and 1.74, while the skewness values

were found to vary between -.66 and.39 (see Table 1). These findings indicate that the assumption of normality was met in this study (Kline, 2019).

This study examined multicollinearity assumption through VIF, tolerance, and correlation analysis. While the tolerance value of this study was.91, the VIF value was determined as 1.09. In addition, this study's correlation analysis findings of both observed and latent variables did not reveal a relationship of.90 and above (see Table 1 and Table 2). All these findings prove that there is no multicollinearity problem in this study (Kline, 2019).

3.2 Two-stage structural equation modeling analysis

This study aims to examine the mediating role of individual innovativeness in the relationship between career engagement and AI anxiety. For this aim, the data were evaluated through two-stage structural equation modeling. At this point, the measurement model test was applied in the first stage. After the measurement model proved compatible with the data, the structural model test was performed in the second stage (Anderson & Gerbing, 1988).

3.2.1 Measurement model testing (Stage 1)

This study was designed with three latent variables (Career Engagement, Individual Innovativeness, and AI Anxiety) and ten observed variables (Parcels 1 and 2 of Career Engagement, Risk-Taking, Openness to Experience, Opinion-Leading, Resistance to Change, Learning, Job Replacement, Sociotechnical Blindness, and AI Configuration). When the measurement model test was applied, it was found that the goodness of fit values [$\chi 2/df$= 1.34; AGFI =.94; NFI =.96; GFI =.96, CFI =.99 and RMSEA =.03] were at a good level. In addition, the standardized factor loadings of the measurement model ranged from -.25 to.97, and all t-values were significant (see Fig. 2 and Table 3).

3.2.2 Structural model testing (Stage 2)

The Partial Mediation Structural Model (MODEL A) test was first conducted in this section. As a result of the analysis, the Partial Mediation Structural Model (MODEL A) showed a good fit [$\chi 2/df$= 1.34; AGFI =.94; NFI =.96; GFI =.96, CFI =.99 and RMSEA =.03]. However, the path to Career Engagement ➔ AI Anxiety was insignificant (β = -.05, t= -.609, p>.05).

Secondly, the path to Career Engagement ➔ AI Anxiety was removed because it was meaningless. The analysis was conducted again. As a result of the Full Mediation Structural Model (MODEL B) test, goodness of fit values [$\chi 2/df$= 1.31; AGFI =.94; NFI =.96; GFI =.96, CFI =.99 and RMSEA =.03] were found to be at a good level.

Finally, the best model was decided by looking at the Chi-square difference test and model comparison goodness of fit values (ECVI and AIC). In the Chi-square difference test, the path from Career Engagement to AI Anxiety was removed from the model. It was found that the path did not contribute significantly to the model ($\Delta\chi^2$ =.03, df = 1, p >.05). In addition, the comparison goodness of fit values of Model B

Table 1 Descriptive statistics and correlation analysis of observed variables

Variables	1	2	3	4	5	6	7	8	9	10
1. CEp1	1									
2. CEp2	.780**	1								
3. Resistance to Change	-.199**	-.073	1							
4. Opinion-Leading	.364**	.296**	-.152*	1						
5. Openness to Experience	.459**	.380**	-.229**	.616**	1					
6. Risk-Taking	.256**	.253**	-.023	.267**	.401**	1				
7. Learning	-.188**	-.116	.114	-.089	-.190**	-.129*	1			
8. Job Replacement	-.148*	-.069	.095	-.105	-.130*	-.132*	.427**	1		
9. Sociotechnical Blindness	-.116	-.099	.064	-.171**	-.180**	-.139*	.395**	.817**	1	
10. Artificial Intelligence Configuration	-.147*	-.095	.096	-.171**	-.175**	-.130*	.351**	.695**	.742**	1
Arithmetic M.	18.10	13.67	21.96	17.67	19.50	6.78	11.07	12.85	13.04	8.72
SD	3.39	3.07	4.95	3.18	2.90	1.45	4.00	3.83	3.86	3.41
Kurtosis	.13	-.28	.63	.44	1.74	.53	-.13	-.19	-.11	-.98
Skewness	-.26	-.22	.05	-.11	-.66	-.28	.39	-.59	-.62	-.10

**$p<.01$, *$p<.05$

Table 2 Correlation analysis of latent variables

Variables	1	2	3
1. Career Engagement	1		
2. Individual Innovativeness	.292**	1	
3. Artificial Intelligence Anxiety	-.160**	-.111	1

**p<.01

(ECVI =.317, AIC = 87.386) are smaller than Model A (ECVI =.323, AIC = 89.024) (see Table 4). As a result, these findings prove that the Full Mediation Structural Model (MODEL B) is the best model.

A one-unit increase in Career Engagement is related to a 0.54 unit increase (t=5.188; p<.001) in Individual Innovativeness. Finally, a one-unit increase in Individual Innovativeness was related to a 0.23 unit (t=−2.928; p<.01) decrease in AI Anxiety. When the explained variances (R^2) were evaluated, Career Engagement accounted for approximately 29% of Individual Innovativeness. Career Engagement and Individual Innovativeness together explain about 5% of AI Anxiety (see Fig. 3 and Table 5).

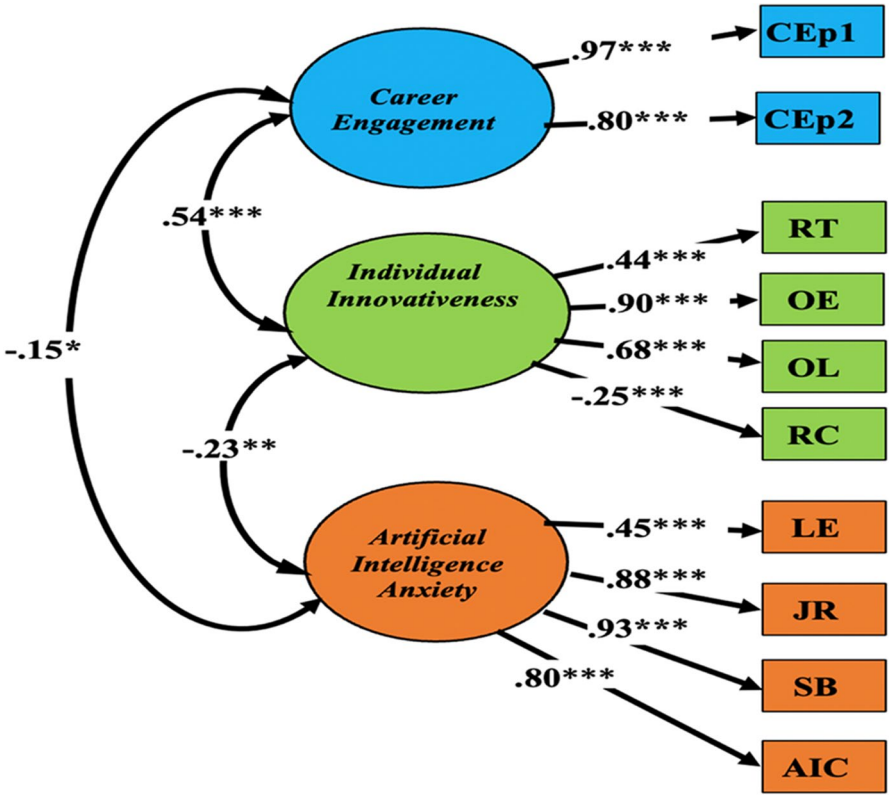

Fig. 2 Path diagram of measurement model. Note. ***p<.001; **p<.01, *p<.05; CEp1, CEp2= Parcels of Career Engagement, RT: Risk-Taking, OE: Openness to Experience, OL: Opinion-Leading, RC: Resistance to Change, LE: Learning, JR: Job Replacement, SB: Sociotechnical Blindness, AIC: Artificial Intelligence Configuration

Table 3 Unstandardized factor loadings, standard errors, and t-values of measurement model

Predicted		Predictor	Estimate	S.E.	C.R.	p
Learning	<---	Artificial Intelligence Anxiety	1.000			
Job Replacement	<---	Artificial Intelligence Anxiety	1.884	.245	7.684	***
Sociotechnical Blindness	<---	Artificial Intelligence Anxiety	1.992	.257	7.752	***
Artificial Intelligence Configuration	<---	Artificial Intelligence Anxiety	1.515	.203	7.453	***
Parcel 2 of Career Engagement	<---	Career Engagement	.744	.071	10.469	***
Parcel 1 of Career Engagement	<---	Career Engagement	1.000			
Risk-Taking	<---	Individual Innovativeness	1.000			
Openness to Experience	<---	Individual Innovativeness	4.092	.624	6.557	***
Opinion-Leading	<---	Individual Innovativeness	3.422	.523	6.548	***
Resistance to Change	<---	Individual Innovativeness	−1.947	.558	−3.487	***

***$p<.001$

In the current study, gender was defined as a dummy variable with Female (1) and Male (0) coding. The analysis revealed that gender significantly predicted Career Engagement (β = 0.13, p <0.05). On the other hand, gender did not significantly predict Individual Innovativeness (β = −0.11, p >0.05) and AI Anxiety (β = 0.05, p >0.05).

3.3 Bootstrap analysis (significance of mediating effect of individual innovativeness)

This study aims to examine the mediating role of individual innovativeness in the relationship between career engagement and AI anxiety. Within the scope of this aim, 1000 resampling was performed, and lower and upper-bound confidence intervals were created (Hayes, 2017). The findings of the bootstrapping analysis are given in Table 6.

Table 6 presents the bootstrapping analysis findings of the Full Mediation Structural Model (MODEL B[a]). Accordingly, the mediation effect of Individual Innovativeness is significant (β = -.125, SE=.044 [95% CI =-.220, -.047, p<.05]. All these findings prove that the mediation effect of Individual Innovativeness in the relationship between Career Engagement and AI Anxiety is significant. The evaluation of research hypothesis is presented in Table 7.

4 Discussion

The aim of this study is to investigate the mediating role of individual innovativeness in the relationship between career engagement and AI anxiety. In the mediation analysis conducted for this purpose, it was found that individual innovativeness partially mediates the relationship between students'career engagement and their AI anxiety.

Table 4 Fit measure among competing models

Fit Measure	Good Fit Criteria	MODEL A	***MODEL B[a]***
χ^2/df	$0 \leq \chi 2/df \leq 2$	1.34	***1.31***
RMSEA	$0 \leq RMSEA \leq .05$	.03	***.03***
NFI	$.95 \leq NFI \leq 1.00$	.96	***.96***
GFI	$.95 \leq GFI \leq 1.00$	.96	***.96***
AGFI	$.90 \leq AGFI \leq 1.00$	.94	***.94***
CFI	$.97 \leq CFI \leq 1.00$	.99	***.99***
ECVI	smaller than ECVI for comparison model	.323	***.317***
AIC	smaller than AIC for comparison model	89.024	***87.386***

Source: (Schermelleh-Engel et al., 2003). [a]Represents the best-fitting model

The hypotheses of the current study have been interpreted within the framework of the literature below.

4.1 Career engagement and individual innovativeness

The first hypothesis (H1) of the study,"Career Engagement is a significant predictor of individual innovativeness,"was confirmed, indicating that students'career engagement significantly explains their individual innovativeness. Accordingly, as

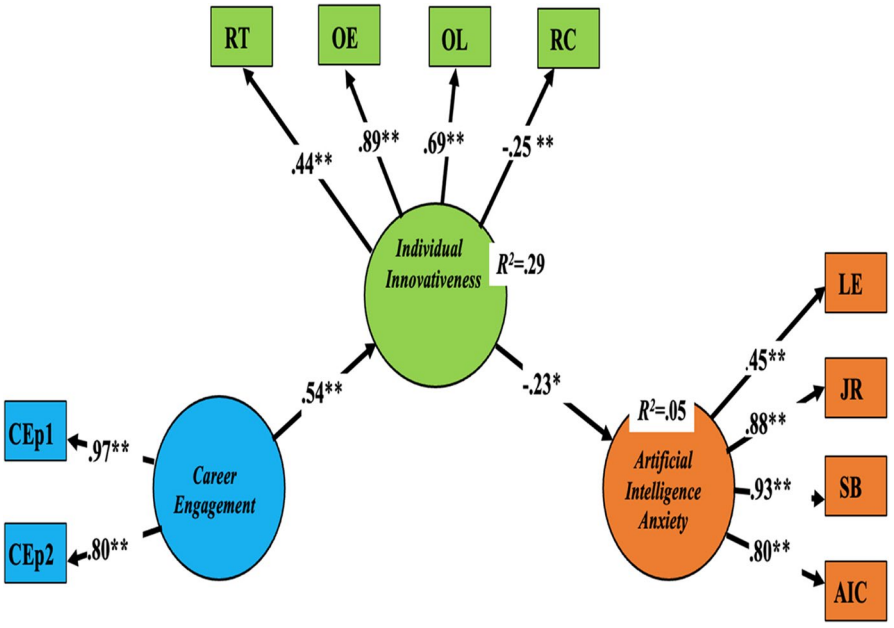

Fig. 3 Path diagram of full mediation structural model (MODEL B[a]). Note. **p<.001, *p<.01, CEp1, CEp2= Parcels of Career Engagement, RT: Risk-Taking, OE: Openness to Experience, OL: Opinion-Leading, RC: Resistance to Change, LE: Learning, JR: Job Replacement, SB: Sociotechnical Blindness, AIC: Artificial Intelligence Configuration

Table 5. Unstandardized path coefficients of full mediation structural model (MODEL B[a])

Predicted		Predictor	Estimate	S.E.	C.R.	p
Individual Innovativeness	<---	Career Engagement	.104	.020	5.188	**
Artificial Intelligence Anxiety	<---	Individual Innovativeness	-.649	.222	−2.928	.003*
Learning	<---	Artificial Intelligence Anxiety	1.000			
Job Replacement	<---	Artificial Intelligence Anxiety	1.884	.246	7.674	**
Sociotechnical Blindness	<---	Artificial Intelligence Anxiety	1.996	.258	7.744	**
Artificial Intelligence Configuration	<---	Artificial Intelligence Anxiety	1.516	.204	7.445	**
Parcel 2 of Career Engagement	<---	Career Engagement	.747	.071	10.485	**
Parcel 1 of Career Engagement	<---	Career Engagement	1.000			
Risk-Taking	<---	Individual Innovativeness	1.000			
Openness to Experience	<---	Individual Innovativeness	4.065	.617	6.586	**
Opinion-Leading	<---	Individual Innovativeness	3.424	.523	6.552	**
Resistance to Change	<---	Individual Innovativeness	−1.946	.558	−3.488	**

**p<.001, *p<.01

the level of career engagement increases, so does the level of individual innovativeness. Studies examining the relationship between career engagement and individual innovativeness have shown a positive relationship, suggesting that career engagement contributes to the emergence of innovative behaviors (Agarwal et al., 2012; Al-Hawari et al., 2019; Ali et al., 2022; Kim & Park, 2017; Nguyen & Petchsawang, 2024; Sharma & Nambudiri, 2020; Wu & Wu, 2019; Zhu et al., 2018).

When examining the definitions of career engagement and individual innovativeness, it is seen that these concepts are closely related. Innovators who are early adopters of technology are independent decision-makers guided more by their own personalities than by the opinions of others regarding a new product (Truong, 2013). Researchers agree that proactive personality benefits innovative behavior (Rodrigues & Rebelo, 2019; Su & Zhang, 2020). Therefore, individuals showing career engagement and individual innovativeness share the common trait of exhibiting proactive behavior. Proactive behavior is inherently focused on change and the future; thus, proactive individuals are highly likely to follow innovations related to their careers, explore development opportunities, and participate in learning environments that

Table 6. Bootstrapping analysis results of full mediation structural model (MODEL B[a])

Model pathways	Bootstrap values		Bias 95% CI		p
	β	SE	Lower Bounds	Upper Bounds	
Mediator Effect					
CE ➔ II➔ AIA	-.125	.044	-.220	-.047	.002

*p<.05; β Standardized coefficients, *SE* Standard Error; *CE* Career Engagement, *II* Individual Innovativeness

AIA Artificial Intelligence Anxiety, Bootstrap is based on 1000 resamples (Hayes, 2017)

Table 7 Evaluation of research hypotheses

Hypotheses	Model pathways	β	Effect Size	Decision
	Direct effect			
H[1]	CE ➔ II	.54	High	Supported
H[2]	II ➔ AIA	-.23	Medium	Supported
H[3]	CE ➔ AIA	-.05	Low	Unsupported
	Indirect Effect			
H[4]	CE ➔ II ➔ AIA	-.12	Medium	Supported
	Total Effect			
	CE ➔ AIA	-.17	Medium	

CE Career Engagement, *II* Individual Innovativeness, *AIA* Artificial Intelligence Anxiety, Path coefficients effect size as low below.10, medium below.30 and high above.50 (Kline, 2019)

support their careers (Bateman & Crant, 1993). The millennial generation, in particular, is likely to make more efforts to accept new ideas, be original, and acquire new knowledge and skills (Zhu et al., 2018). Proactive individuals tend to be innovative, open to learning, and possess strong problem-solving skills, often creating positive change in their environment regardless of situational constraints (Seibert et al., 2001). Since innovative behaviors involve producing something new, they require individuals to focus on their career goals and take action accordingly (Agarwal et al., 2012). Therefore, individuals showing higher levels of career engagement are more likely to be original, innovative, and take initiative in problem-solving than others. Consequently, career engagement necessitates active work related to the profession one chooses, which triggers innovativeness.

4.2 Individual innovativeness and artificial intelligence anxiety

The second hypothesis (H2) of the study,"Individual Innovativeness is a significant predictor of AI anxiety,"was confirmed, proving that students'individual innovativeness predicts their AI anxiety. Accordingly, as the level of individual innovativeness increases, the level of AI anxiety decreases. Relevant literature indicates that personality traits significantly predict AI anxiety, showing that individual innovativeness increases positive attitudes toward AI technologies (Dwivedi et al., 2021; Gansser & Reich, 2021; Kaya et al., 2022; Northeastern University, 2018; Park et al., 2022).

AI is seen as an innovative technology capable of leading to profound changes that can enhance productivity, efficiency, and competitiveness of individuals or institutions (Presbitero & Teng-Calleja, 2022; Wang & Wang, 2019). While AI's potential to improve life in various fields such as healthcare, customer service, and education is increasingly accepted (Kim & Lee, 2024), potential risks, negative impacts, and uncertainties associated with the use of AI in various social fields can cause discomfort and fear regarding AI (Agogo & Hess, 2018; Li & Huang, 2020; Wang & Wang, 2019). AI anxiety can be attributed to concerns about its negative aspects, such as employment issues, privacy and transparency, security, socioeconomic inequalities, unethical behaviors, passive individualization, and biased or discriminatory outcomes (Green, 2020; Hopcan et al., 2024; Li & Huang, 2020; Park et al., 2022; Terzi, 2020).

Personality traits, defined as relatively stable tendencies shaping thoughts, emotions, and behaviors, are known to predict AI anxiety (Devaraj et al., 2008). Individuals form beliefs about new technologies based on personal dispositions (Agarwal

& Prasad, 1998), and their perceptions, whether viewing technology as useful or threatening, affect their attitudes and behaviors (Liang & Xue, 2010). Among personality traits, individual innovativeness plays a key role in shaping positive technology perceptions (Agarwal & Prasad, 1998; Rogers & Shoemaker, 1971). Innovative individuals tend to be more open to change, proactive in exploring new technologies, and less susceptible to anxiety stemming from unfamiliarity (Gansser & Reich, 2021). In contrast, those with limited curiosity or technological experience may lack critical awareness, heightening uncertainty and fear (Zainal & Newman, 2023). Thus, a strong interest in technology is generally associated with more favorable attitudes towards AI (Hopcan et al., 2024; Sanusi et al., 2022).

4.3 Career engagement and artificial intelligence anxiety

The third hypothesis (H3), positing that career engagement would significantly predict AI anxiety, was not supported. Although no prior study appears to have directly investigated the relationship between career engagement and AI anxiety, existing research provides indirect evidence through related constructs such as proactive personality, which is conceptually aligned with career engagement. Prior studies generally report a negative relationship between proactive traits and anxiety (Feng & Zhang, 2025; Huang et al., 2020; Salimi et al., 2025; Ugwu et al., 2021), suggesting that individuals who actively manage their career development should experience less anxiety. However, this association appears to vary across contexts. For instance, while Kilic et al. (2024) found no significant relationship between proactive personality and anxiety among undergraduate students in Turkey, Yeşiltaş and Andiç (2021) observed a weak negative correlation in a working adult sample, and Akbaba and Özel (2021) even reported a moderate positive correlation in a tourism student sample. These conflicting findings indicate that the relationship between proactive dispositions and anxiety is neither stable nor universal.

The lack of support for H3 in this particular study may reflect the unique characteristics of the sample, university students in education, health sciences, and psychology. These disciplines are known for their heavy reliance on emotional labor, interpersonal interaction, and professional judgment. According to Frey and Osborne (2017), occupations in such domains face relatively low automation risk due to their demand for social and emotional competencies. Consequently, students in these fields may perceive AI as less threatening to their future employment prospects, thereby weakening the association between career engagement and AI anxiety. Similarly, Autor (2015) highlights that AI technologies are more likely to replace routine cognitive and manual tasks than emotionally nuanced roles.

In this regard, the findings may be further interpreted through the lens of the Transactional Theory of Stress (Lazarus & Folkman, 1984), which emphasizes that individuals' cognitive appraisal of threats is shaped by both personal and environmental resources. Career engagement, as an internal resource, may not be sufficient to mitigate anxiety if external conditions, such as perceived low risk of automation or strong social support, buffer perceived threats. This may be especially relevant in Turkey's collectivist cultural context, where family networks, peer solidarity, and state-backed programs often serve as informal social safety nets. These external sup-

ports may attenuate the effect of career engagement on anxiety, making the direct relationship statistically insignificant.

Moreover, Psychological Capital (Luthans et al., 2006), which is a composite construct encompassing self-efficacy, optimism, hope, and resilience, has been shown to enhance individuals'ability to cope with workplace challenges, including technological disruption.

According to Social Cognitive Theory (Bandura, 1986), individuals with high technological self-efficacy tend to experience lower levels of technostress and demonstrate better psychological adjustment (Kim & Lee, 2025). Resilience and hope are critical factors contributing to the well-being of emerging adult university students. While resilience enables students to quickly analyze problems, generate solutions, and adapt to new situations, hope assists them in managing potential stress, alleviating concerns about the future, and maintaining focus on their success goals (Eren et al., 2025). These insights suggest that personal psychological resources may serve as more immediate buffers against AI-related anxiety than career engagement alone.

Additionally, the Career Adaptability framework (Savickas, 2005; Savickas & Porfeli, 2012) proposes that job-related anxiety is shaped not merely by commitment but also by a constellation of psychological and contextual factors, such as cognitive competence, personality traits, self-esteem, future orientation, and positive affectivity. Taken together, these frameworks underscore the need to move beyond unidimensional explanations and adopt a more integrative and contextualized perspective on AI-related anxiety.

Finally, the diverse implications of AI for different sectors must be considered. Research has shown that students' attitudes toward AI are shaped by their disciplinary backgrounds, with some expressing optimism about AI's potential, and others voicing concern over its implications for employment (Bankins et al., 2024; Hopcan et al., 2024). In sectors like banking, customer service, and telemarketing, where AI applications such as chatbots and voice assistants are rapidly advancing, students may experience heightened anxiety due to job insecurity (Acemoglu & Restrepo, 2020; Kaya et al., 2022; Kong et al., 2023; Lin et al., 2024; Wang et al., 2024). However, this pattern is not uniform. Studies indicate that AI anxiety levels vary significantly across disciplines, further supporting the view that career engagement interacts with a host of personal and contextual factors in shaping anxiety outcomes (Brougham & Haar, 2018; Brynjolfsson & McAfee, 2014; Synard & Gazzola, 2018).

In sum, the findings of this study suggest that career engagement in isolation does not significantly predict AI anxiety. Rather, this relationship appears to be moderated by a range of psychological traits (e.g., innovativeness, self-efficacy), demographic factors (e.g., field of study), and cultural-contextual conditions. Taken together, these insights underscore the multifactorial nature of AI-related anxiety and highlight the importance of adopting a nuanced theoretical framework that integrates personal and contextual variables to better understand students' psychological readiness for AI-integrated futures.

4.4 Mediating role of individual innovativeness

The fourth hypothesis (H4) of the study,"The mediating effect of Individual Innovativeness on the relationship between career engagement and AI anxiety is significant,"was confirmed. Findings indicate that individual innovativeness functions as a mediating variable between career engagement and AI anxiety. This suggests that individuals with higher levels of career engagement may better manage AI-related anxiety due to their innovative dispositions. As information and communication technologies proliferate across all sectors (Frey & Osborne, 2017), the competencies required for employment continue to evolve. This digital transformation places greater responsibility on individuals to proactively manage their careers (Hirschi et al., 2013). In such dynamic contexts, career engagement becomes essential, not only for leveraging new opportunities but also for mitigating potential risks. For university students, this entails cultivating proactive attitudes and preparing for both the promises and disruptions that emerging technologies may introduce (Hirschi, 2018).

The mediating role of individual innovativeness in the relationship between career engagement and AI anxiety can be understood through its function as a psychological filter or adaptive resource. While career engagement reflects an individual's proactive stance toward shaping their future career, it does not automatically equip them with the cognitive flexibility or emotional resilience needed to interpret disruptive technologies like AI in a constructive way. Individual innovativeness, which reflects openness to novelty, risk tolerance, and proactive experimentation, plays a pivotal role in shaping how career-engaged individuals respond to such challenges. Innovative individuals are more likely to interpret AI technologies as opportunities for growth, skill enhancement, and professional differentiation, thereby buffering against anxiety. In contrast, those with low innovativeness may perceive AI developments as destabilizing or threatening, even if they are actively engaged in career planning. Therefore, individual innovativeness acts as the transformational mechanism that channels career engagement into either reduced or elevated anxiety about AI.

High career engagement requires individuals to research and make initiatives regarding their future careers, necessitating innovation. Individual innovativeness, by increasing awareness of current technologies, effective and efficient use of them, and adaptation to them, can also help reduce concerns about these technologies. Therefore, innovative individuals with high career engagement may see AI, an innovative technology of today, as a tool that can help them reveal their existing potentials and achieve their career goals rather than perceiving it as a threat to their careers.

Understanding the role of individual innovativeness in the process of perceiving emerging innovations and developing this trait is crucial (Yi et al., 2006). This way, it becomes possible for individuals to manage their concerns when facing innovations, learn how to work effectively with AI instead of focusing on its negative impacts and worrying (Huang et al., 2019). Individuals with high individual innovativeness can adapt more quickly to changes, solve problems they encounter, and come up with new ideas. Moreover, individuals who use information technologies more innovatively are more likely to exhibit positive beliefs about technology use, leading technological transformations (Agarwal & Prasad, 1998).

Interest in innovative technologies such as AI and knowledge accumulation in this field have a significant impact on reducing concerns about these technologies, as stated in the literature (Hopcan et al., 2024; Sanusi et al., 2022). In this context, when the predictive roles of career commitment and individual innovativeness on AI anxiety are examined within the framework of the CCT (Savickas, 2005; Savickas & Porfeli, 2012), it becomes evident that these variables align with one of the model's core components, namely, "career adaptability resources." Specifically, career commitment, which reflects individuals'tendencies to maintain and enhance their professional identity, and individual innovativeness, which denotes the capacity to adapt to changing work environments, appear to serve crucial functions in mitigating anxiety associated with AI. These constructs not only embody the adaptability required in contemporary career development but also contribute to individuals' psychological preparedness in the face of technological transformation.

The TAM (Agarwal & Prasad, 1998; Davis, 1989), which emphasizes the role of perception in technology adoption, demonstrates that individuals'willingness to use technology is largely shaped by their personal characteristics. Similarly, the framework for 21st-century skills proposed by the Partnership for 21 st Century Learning (2007) groups essential competencies for students into three broad domains: learning and innovation skills, life and career skills, and information, media, and technology skills. Notably, individual innovativeness, a personality trait that integrates elements of curiosity and courage (Lu et al., 2005), emerges as a salient construct both within TAM and in frameworks designed to foster 21st-century learning skills. Students who exhibit high levels of individual innovativeness are more likely to seek information about AI tools specific to their disciplines, explore how these technologies function, and actively develop their competencies regarding the integration of AI into their professional fields. This suggests that individual innovativeness not only facilitates technology adoption but also enhances students' readiness to navigate the complexities of AI-driven work environments.

5 Practical implications

Educators and career counselors can minimize AI anxieties by developing strategies to strengthen students'career engagement. In this regard, awareness-raising activities for career planning processes, professional identity development programs, and guidance services for long-term career goals are essential. Career counselors should guide students to see AI as an opportunity rather than a threat in their future careers. In particular, it may be possible to reduce students'uncertainty about AI by focusing on digital skills acquisition and adopting a culture of lifelong learning and flexible career planning.

Future efforts to reduce AI anxiety among students could benefit from semi-experimental intervention programs grounded in the present model's dimensions. Practitioners may design integrative strategies aimed at enhancing students'career engagement and innovativeness to build psychological resilience and facilitate smoother adaptation to technological transitions. Interventions may include the development of AI-integrated career counseling systems offering personalized guid-

ance based on individual interests and abilities, as well as innovation-focused workshops targeting students with lower levels of innovativeness.

In contrast to the standardized, hierarchical, and rigid educational paradigm characteristic of the industrial society, today's knowledge society shaped by the pervasive presence of AI technologies across nearly all occupational domains necessitates a new educational approach centered on dynamic competencies such as entrepreneurship, experimentation, and adaptability. Consequently, it becomes imperative to empower students by providing them with both in-school and out-of-school learning environments that foster AI literacy. Such environments should aim to enhance students' critical understanding, responsible use, and creative engagement with AI, thereby equipping them with the skills required to navigate and shape the rapidly evolving technological landscape.

To support university students in their adaptation to AI, a multifaceted approach must be adopted. During the course of higher education, it is crucial to cultivate students' awareness regarding the impact of AI on their respective fields, inform them about how AI can be integrated into their disciplines, and serve as role models by embedding AI applications within coursework. Furthermore, it is essential to engage students in hands-on projects that involve the application of these models and to expose them, through various means, to future work environments where AI is embedded.

Educators should also work to shift student perceptions of AI from that of a challenge to a development opportunity. This involves designing educational interventions aimed at enhancing AI literacy, such as offering targeted courses, promoting participation in seminars and conferences, and creating opportunities for interdisciplinary collaboration. In particular, AI tools should be incorporated into educational practices in ways that support research, inquiry, problem-solving, and critical thinking. Furthermore, students should be encouraged to undertake innovative project work where ethical and responsible use of AI is emphasized.

In order to enhance students' AI literacy, they should be introduced to digital learning communities specifically designed around AI, and encouraged to participate in AI-focused training opportunities. Additionally, interdisciplinary team-based projects should be promoted as a means to strengthen students' technology-driven problem-solving abilities. In this regard, offering discipline-specific workshops and seminars on the practical applications of AI may positively impact students' levels of innovativeness and deepen their constructive engagement with these technologies. University career centers, in interdisciplinary collaboration with departments such as guidance and psychological counseling, instructional technologies, and software engineering, can design accessible educational modules aimed at developing basic-level AI literacy for all students. In addition, artificial intelligence integration can be tailored within university curricula across different disciplines. For instance, in the field of educational sciences, AI-supported assessment and evaluation systems; in health sciences, automated patient data documentation and clinical decision support mechanisms can be implemented with attention to disciplinary distinctions.

Furthermore, to raise awareness about innovative technologies, universities can partner with future employers to organize on-campus technology festivals, arrange visits to technology fairs, and conduct field trips to pioneering institutions that effec-

tively utilize AI technologies. Additionally, seminars can be held to reduce students' AI-related anxieties and support their career planning. Participation in student symposiums, where students can share innovative ideas that help build career networks, can also be promoted to alleviate future career-related concerns. Finally, policymakers should develop policies that support AI integration into the workforce through university-industry collaboration. Certification programs tailored to the adaptation of AI in various career fields should be established via authorized bodies. Moreover, legal regulations should be enacted to ensure the ethical and responsible use of artificial intelligence.

6 Limitations and future research recommendations

This study employed convenience sampling to recruit university students, as this method allowed efficient access to participants with relevant AI experiences in higher education while accommodating the research's exploratory nature. In addition, the university environment's homogeneous structure also enabled more controlled analysis of variables. However, the convenience sampling method has important limitations. The sample's homogeneity in demographics (age, education level), overrepresentation of women and specific disciplines (health sciences, education), and geographic concentration (three universities in two regions) constrain the findings'generalizability. While appropriate for exploratory research, these limitations could be addressed in future studies through stratified sampling in quantitative studies or maximum diversity sampling in qualitative studies to include broader disciplines (e.g., engineering, art, medicine); expansion to different geographic regions across Turkey and comparative studies with professionals across sectors to enhance the findings'applicability.

This study's cross-sectional design constitutes a key limitation. Future research could employ longitudinal or experimental designs to better validate mediation effects and establish causal relationships Additionally, the study did not conduct subgroup analyses to examine potential differences among students from different academic disciplines or institutions. Subgroup analyses based on variables such as studying in different academic disciplines (e.g. engineering, art, etc.) and university type (e.g. public, private) can be performed in future studies. Using advanced statistical methods such as multi-group SEM, structural relationships across different academic disciplines or institutions can be compared.

Quantitative research designs including other factors influencing AI anxiety in the career process can be planned. Experimental studies designed to integrate AI into students'careers can examine changes in their attitudes toward AI. Also, future experimental studies can also prepare programs that include AI skill-building interventions. Qualitative studies aimed at understanding other factors affecting AI anxiety in students with different levels of career engagement can be planned. This way, a deeper understanding of how contextual factors shape innovativeness levels and attitudes toward AI can be obtained.

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Declarations

Competing interests No potential conflict of interest was reported by the authors.

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