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When Artificial Intelligence Reshapes the Labor Market: The Mediating Role of Career Anxiety in Students' Career Readiness

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Abstract

The rapid adoption of artificial intelligence (AI) has transformed labor market structures and skill requirements, raising concerns about its implications for university students' career development. However, limited research has distinguished between different dimensions of AI-driven change and their psychological effects on career readiness. This study aimed to examine the effects of AI-labor market transformation and skill-based technological change on career anxiety and career readiness among university students, as well as the mediating role of career anxiety. A quantitative cross-sectional design was employed involving 300 undergraduate students in Pontianak, Indonesia. Data were collected using a structured questionnaire and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings indicate that AI-labor market transformation has a significant positive effect on career anxiety, whereas skill-based technological change does not significantly influence career anxiety. Career anxiety positively affects career readiness and significantly mediates the relationship between AI-labor market transformation and career readiness. However, it does not mediate the relationship between skill-based technological change and career readiness. These findings suggest that students are more psychologically affected by uncertainty regarding future employment opportunities than by changes in skill requirements. The study contributes to the literature by conceptualizing AI-driven change into two distinct dimensions and demonstrating that they influence career readiness through different psychological pathways. The findings also provide practical implications for higher education institutions in designing career development initiatives that integrate AI literacy with psychological support to better prepare students for an AI-driven labor market.

Keywords:
Artificial intelligence; AI-labor market transformation; Career anxiety; Career readiness; Skill-based technological change.

1. INTRODUCTION

Digital transformation, driven by the rapid advancement of artificial intelligence (AI), has triggered structural changes in the global labor market and economic systems. AI-based automation has been increasingly adopted to enhance efficiency, productivity, and industrial competitiveness (Czarnitzki et al., 2023; Fawwaz et al., 2025; Kassa & Worku, 2025). From a human resource economics perspective, however, the adoption of AI has also reshaped labor demand by reducing the need for routine occupations while increasing demand for new competencies that are adaptive, cognitive, and technology-oriented (Lábaj et al., 2025). These transformations position AI as a critical determinant of human capital value and the evolving dynamics of human capital development within the AI-driven economy (Fan et al., 2025; Kholifah et al., 2025; Liu & Li, 2024).

Within this context, university students, as the future workforce, represent a strategically important group in the economic system. They are expected to experience the direct consequences of AI-driven job automation, particularly when a mismatch exists between the competencies acquired through higher education and the evolving demands of the labor market (Alogla, 2025; Xiao et al., 2025). From a human resource economics perspective, such a mismatch may diminish the value of human capital and weaken regional workforce competitiveness. Consequently, students' career readiness has become a critical economic concern, as it reflects individuals' capacity to enter and participate productively in a labor market undergoing rapid digital transformation (Coetzee, 2023).

The influence of AI-driven job automation on students' career readiness is likely to occur indirectly through career anxiety. In the present study, AI-driven job automation is represented by the constructs of skill-based technological change and AI-labor market transformation. Specifically, perceptions of labor market risks associated with AI automation may increase career anxiety, which subsequently affects students' preparedness to navigate an AI-driven labor market. Moreover, the accelerating pace of AI-based automation has intensified uncertainty within labor markets. This uncertainty may alter individuals' economic expectations regarding employment opportunities and the returns on educational investment. Previous studies suggest that perceptions of AI's impact on employment can trigger career anxiety, which, from a labor economics perspective, can be interpreted as a rational response to perceived labor market risk (Uçar et al., 2025; Üstün & Danacıoğlu, 2026). Empirical evidence further demonstrates that AI-related career anxiety significantly influences students' career decision clarity, highlighting the crucial role of perceived economic risk in shaping individual career behavior (Yaşar & Karagucuk, 2025).

Career anxiety should not be viewed solely as a psychological phenomenon but also as an economic mechanism that influences career decision-making and individuals' readiness to enter the labor market. Recent studies have reported that the growing uncertainty associated with AI and automation may reduce individuals' economic confidence, hinder career planning, and weaken work readiness (Chen et al., 2025; Li et al., 2025). Accordingly, career anxiety may serve as an important mediating mechanism linking AI-induced structural changes in the labor market to career readiness as a human capital outcome.

The effect of AI-driven job automation on students' career readiness is therefore unlikely to be entirely direct but may operate through career anxiety. Through the dimensions of skill-based technological change and AI-labor market transformation, AI-driven automation influences students' perceptions of labor market risk, which shape their level of career anxiety and subsequently affect their career readiness. Higher levels of perceived labor market risk are expected to increase career anxiety and reduce career readiness, whereas the ability to manage labor market uncertainty is likely to enhance students' preparedness for an AI-driven labor market. This study addressed the following research questions:

a. Does skill-based technological change significantly influence career anxiety among university students in Pontianak City?
b. Does AI-labor market transformation significantly influence career anxiety among university students in Pontianak City?
c. Does career anxiety significantly influence career readiness among university students in Pontianak City?
d. Does career anxiety mediate the relationship between skill-based technological change and career readiness among university students in Pontianak City?
e. Does career anxiety mediate the relationship between AI-labor market transformation and career readiness among university students in Pontianak City?

2. RESEARCH METHOD

This study employed a quantitative approach using an analytical survey design to examine the direct and indirect effects of AI-driven job automation on university students' career readiness, with career anxiety serving as a mediating variable.

The population comprised undergraduate students enrolled in non-STEM programs within the social sciences and humanities disciplines at universities in Pontianak City, Indonesia. Participants were selected using purposive sampling based on the following criteria: (1) active undergraduate students and (2) enrolled in the fourth to eighth semester. Students who were not actively enrolled or did not meet the specified semester criteria were excluded from the study. The minimum sample size was determined according to the 10-times rule for Partial Least Squares Structural Equation Modeling (PLS-SEM) (Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, 2017), which recommends a minimum sample equivalent to ten times the number of indicators associated with the most complex construct.

Data were collected using a structured questionnaire with a five-point Likert scale to measure four latent constructs: skill-based technological change, AI-labor market transformation, career anxiety, and students' career readiness. The skill-based technological change and AI-labor market transformation constructs were conceptualized as two complementary dimensions of AI-driven job automation. The SBTC construct was developed based on the perspective of skill-biased technological change, which explains shifts in the economic value of human capital resulting from technological advancement (Battisti et al., 2022). Meanwhile, the ALMT construct was developed from the perspective of AI-labor market transformation, which explains structural changes in employment demand, occupational composition, and labor market dynamics resulting from the adoption of intelligent technologies (Choi & Leigh, 2024; Zhou et al., 2025). The career anxiety construct was grounded in career construction theory, which conceptualizes career anxiety as an adaptive response to uncertainty, perceived labor market risks, and career instability arising from technological disruption (Savickas, 2013). Meanwhile, the students' career readiness construct was based on the contemporary employability and career readiness framework, emphasizing adaptive readiness, reskilling, and lifelong learning capabilities as essential dimensions of human capital in the AI-driven economy (Fugate et al., 2021; Testa et al., 2026).

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software. The analysis involved the evaluation of both the measurement model and the structural model. The measurement model was assessed in terms of convergent validity, discriminant validity, and construct reliability, whereas the structural model was evaluated using path coefficients. Direct and indirect effects were examined using the bootstrapping procedure, with statistical significance determined at a p-value of < 0.05 (Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, 2017). The research instrument constructs are presented in Table 1.

Table 1. Research Instrument Constructs

Variable	Construct	Indicator	Underpinned Theories
Skill-Based Technological Change			1.1.1
	SBTC1	Perceived task automation by AI	(Autor et al., 2003)
	SBTC2	Perceived AI impact on future employment	
	SBTC3	Perceived future job displacement by AI	
	SBTC4	Importance of technological skills for future employability	
	SBTC5	Increasing demand for digital competencies	
AI-Labor Market Transformation			
	ALMT1	Perceived demand for AI adaptability	(Acemoglu & Restrepo, 2019; Dong & McIntyre, 2014; Frey & Osborne, 2017)
	ALMT2	Perceived future labor market competition	
	ALMT3	Perceived changing value of human skills	
Career Anxiety			1.1.2
	CA1	Concern about future career opportunities	1.1.3 (Savickas, 2013)
	CA2	Uncertainty about future employment prospects	
	CA3	Concern over career uncertainty	
	CA4	Fear of future skill obsolescence	
	CA5	Fear of losing competitiveness in the future labor marke	
	CA7	Concern about future job stability	
Career Readiness			
	CR1	Readiness to adapt to future workplace changes	(Caballero et al., 2011; Fugate et al., 2021).
	CR2	Confidence in adapting to emerging technologies	
	CR3	Willingness to reskill and upskill	
	CR4	Readiness to develop digital competencies	
	CR5	Proactive career information seeking	
	CR6	Lifelong learning awareness	
	CR7	Motivation for lifelong learning	
	CR8	Confidence in future employability	

3. RESULTS AND DISCUSSION

3.1. Respondents' Demographic Characteristics

The findings are presented sequentially, beginning with the respondents' demographic characteristics, followed by the assessment of the measurement model and the structural model.

Table 2. Demographic Characteristics of Respondents (N = 300)

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	92	30.7
	Female	208	69.3
Age	18–20 years	235	78.3
	21–23 years	56	18.7
	>23 years	9	3.0

Table 2 presents the demographic characteristics of the study participants. The final sample consisted of 300 undergraduate students. Of these, 208 (69.3%) were female and 92 (30.7%) were male. The majority of participants were aged 18–20 years (78.3%), followed by those aged 21–23 years (18.7%), while only a small proportion (3.0%) were over 23 years of age.

Following the respondent profile, the measurement model was first assessed by examining the outer loading values of all indicators. Table 3 presents the results of the indicator reliability assessment.

Table 3. Outer Loading

	ALMT	CA	CR	SBTC
ALMT1	0.880			
ALMT2	0.828			
ALMT3	0.833			
CA1		0.824		
CA2		0.797		
CA3		0.843		
CA4		0.842		
CA5		0.831		
CA7		0.850		
CA8		0.848		
CR1			0.770	
CR2			0.838	
CR3			0.886	
CR4			0.912	
CR5			0.789	
CR6			0.850	
CR7			0.853	
CR8			0.849	
SBTC2				0.755
SBTC3				0.753
SBTC4				0.787
SBTC5				0.737
SBTC1				0.762

The outer loading results demonstrated that all indicators achieved values above the recommended threshold of 0.70, ranging from 0.737 to 0.912 (Table 3). This indicates that each indicator adequately represented its respective construct and exhibited satisfactory indicator reliability, providing strong evidence of convergent validity.

3.2. Measurement Model Evaluation

Following the assessment of indicator reliability, construct reliability and convergent validity were evaluated using Cronbach's alpha, composite reliability (ρa and ρc), and average variance extracted (AVE). The results are presented in Table 4.

Table 4. Construct Reliability and Convergent Validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
ALMT	0.803	0.804	0.884	0.718
CA	0.928	0.937	0.941	0.695
CR	0.942	0.944	0.952	0.713
SBTC	0.817	0.822	0.872	0.576

As shown in Table 4, all constructs demonstrated satisfactory internal consistency, with Cronbach's alpha values ranging from 0.803 to 0.942, exceeding the recommended threshold of 0.70. Similarly, composite reliability values (ρa and ρc) were above 0.70 for all constructs, indicating good construct reliability. The AVE values ranged from 0.576 to 0.718, all exceeding the recommended threshold of 0.50, thereby confirming adequate convergent validity of the measurement model.

3.3. Structural Model Assessment

After confirming the adequacy of the measurement model, the structural model was evaluated using the bootstrapping procedure to examine the significance of the proposed relationships among the latent constructs. The assessment focused on the path coefficients, t-statistics, and p-values to determine whether the hypothesized relationships were statistically supported. The results of the structural model assessment are presented in Table 5.

Table 5. Path Coefficients

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
ALMT -> CA	0.385	0.384	0.080	4.803	0.000
CA -> CR	0.196	0.207	0.078	2.528	0.011
SBTC -> CA	0.147	0.156	0.086	1.716	0.086

As shown in Table 5, AI-labor market transformation had a positive and statistically significant effect on career anxiety ($\beta = 0.385$, $t = 4.803$, $p < 0.001$). This finding indicates that greater perceptions of AI-induced transformation in the labor market are associated with higher levels of career anxiety among university students. Career anxiety also exhibited a positive and significant effect on career readiness ($\beta = 0.196$, $t = 2.528$, $p = 0.011$), suggesting that career anxiety plays a significant role in explaining students' preparedness for entering the labor market.

In contrast, the relationship between skill-based technological change and career anxiety was positive but not statistically significant ($\beta = 0.147$, $t = 1.716$, $p = 0.086$). Therefore, the findings do not provide sufficient evidence to support the proposed effect of skill-based technological change on career anxiety. Overall, the structural model supports the significant effects of AI-labor market transformation on career anxiety and career anxiety on career readiness, whereas the effect of skill-based technological change on career anxiety is not supported.

To further examine the proposed mediation mechanism, the indirect relationships among the constructs were analyzed using the bootstrapping procedure. The significance of each indirect path was determined by evaluating the path coefficients, t-statistics, and corresponding p-values. The results of the specific indirect effects are reported in Table 6.

Table 6. Specific Indirect Effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
ALMT -> CA -> CR	0.076	0.080	0.035	2.179	0.029
SBTC -> CA -> CR	0.029	0.035	0.025	1.134	0.257

The mediation analysis revealed that career anxiety significantly transmitted the effect of AI-labor market transformation to career readiness ($\beta = 0.076$, $t = 2.179$, $p = 0.029$). This result suggests that students who perceive greater AI-driven changes in the labor market tend to experience higher career anxiety, which subsequently contributes to their career readiness.

Conversely, the indirect pathway from skill-based technological change to career readiness through career anxiety was not statistically significant ($\beta = 0.029$, $t = 1.134$, $p = 0.257$). Accordingly, career anxiety did not function as a significant mediator in the relationship between skill-based technological change and career readiness. These findings indicate that the mediating mechanism of career anxiety was evident only for the influence of AI-labor market transformation on career readiness.

To provide a comprehensive understanding of the overall relationships among the constructs, the total effects were examined by combining both the direct and indirect effects estimated through the bootstrapping procedure. The results are presented in Table 7.

Table 7. Total Effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
ALMT -> CA	0.385	0.384	0.080	4.803	0.000
ALMT -> CR	0.076	0.080	0.035	2.179	0.029
CA -> CR	0.196	0.207	0.078	2.528	0.011
SBTC -> CA	0.147	0.156	0.086	1.716	0.086
SBTC -> CR	0.029	0.035	0.025	1.134	0.257

Table 7 shows that AI-labor market transformation exerted a significant total effect on both career anxiety ($\beta = 0.385$, $p < 0.001$) and career readiness ($\beta = 0.076$, $p = 0.029$). Career anxiety also demonstrated a significant positive total effect on career readiness ($\beta = 0.196$, $p = 0.011$). In contrast, the total effects of skill-based technological change on career anxiety ($\beta = 0.147$, $p = 0.086$) and career readiness ($\beta = 0.029$, $p = 0.257$) were not statistically significant. These findings indicate that AI-labor market transformation represents the primary AI-related factor influencing students' career readiness, both directly through career anxiety and in terms of its overall effect. Taken together, the results indicate that AI-labor market transformation plays a more prominent role than skill-based technological change in explaining students' career anxiety and career readiness.

The overall structural relationships among the constructs are illustrated in Figure 1, which presents the final PLS-SEM model based on the bootstrapping results.

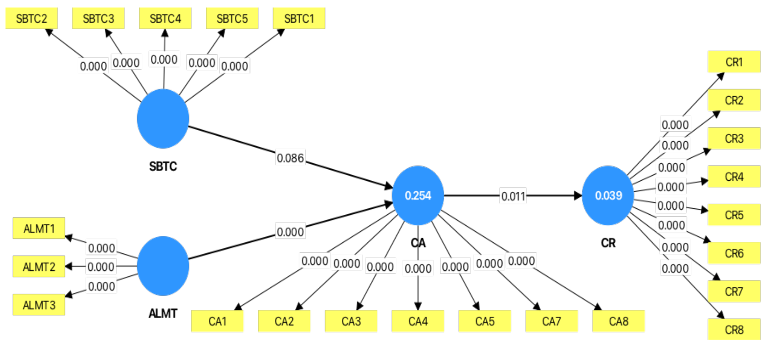

Figure 1. Structural Model

The final structural model confirms that AI-labor market transformation significantly predicts career anxiety, whereas skill-based technological change does not. In addition, career anxiety significantly predicts career readiness and mediates the relationship between AI-labor market transformation and career readiness.

Overall, the findings provide clear answers to the research questions proposed in this study. Skill-based technological change was not found to significantly influence career anxiety among university students in Pontianak City Indonesia, whereas AI-labor market transformation had a significant positive influence on career anxiety. Furthermore, career anxiety significantly enhanced career readiness. The mediation analysis revealed that career anxiety did not mediate the relationship between skill-based technological change and career readiness but significantly mediated the relationship between AI-labor market transformation and career readiness. These findings establish career anxiety as an important psychological mechanism linking AI-driven labor market transformation to students' career readiness.

The findings of this study indicate that AI-labor market transformation significantly increases university students' career anxiety, whereas skill-based technological change does not have a significant effect on career anxiety. This result suggests that students' psychological concerns regarding artificial intelligence are primarily associated with uncertainty about future employment opportunities rather than with changes in workplace skill requirements. In other words, students appear to be more concerned about how AI may transform the availability, stability, and structure of future jobs than about the necessity of developing new technological competencies (Felten et al., 2021; Fu & Zhang, 2026).

The different effects of these two dimensions of AI-driven job automation provide an important insight into how university students perceive technological disruption. AI-labor market transformation represents broader changes in employment structures, occupational opportunities, and future career prospects, whereas skill-based technological change reflects the increasing demand for specific competencies required in AI-enhanced workplaces. The significant influence of AI-labor market transformation indicates that students interpret AI as a potential source of uncertainty regarding their future career pathways. This finding is consistent with previous studies suggesting that AI-related transformation affects career trajectories by shaping individuals' perceptions of future employment opportunities, career exploration processes, and career management strategies (Bankins, Jooss, et al., 2024; Duan et al., 2026).

From a career psychology perspective, the findings highlight the important role of uncertainty in explaining students' career anxiety. When students perceive that AI may substantially reshape employment opportunities, they may experience difficulties in predicting future career conditions and evaluating whether their current educational preparation will remain relevant. Previous research has demonstrated that AI-related uncertainty can increase career anxiety by reducing individuals' confidence in career planning and future career decision-making (Yaşar & Karagucuk, 2025). Therefore, the present study extends previous findings by demonstrating that perceived labor market transformation, rather than technological skill change alone, represents a stronger psychological trigger of career anxiety among university students.

The findings can also be interpreted through the perspective of human capital theory. University students invest time and resources in education with the expectation that their knowledge, skills, and qualifications will provide future career benefits (Kholifah et al., 2025; Yubilianto, 2020). However, when AI is perceived as transforming employment structures, students may become uncertain about the future value of their accumulated human capital. Such uncertainty may occur because students are not only concerned about whether they possess adequate skills but also whether those skills will continue to be valued in an AI-driven labor market (Bankins, Hu, et al., 2024; Felten et al., 2021). Therefore, career anxiety emerges from uncertainty about the future return of educational investment rather than simply from the requirement to acquire additional competencies.

In contrast, the insignificant relationship between skill-based technological change and career anxiety suggests that students may perceive changing skill requirements as a manageable and expected aspect of career development. The increasing importance of digital competencies, AI literacy, and technological adaptability may be understood as necessary forms of professional development rather than as direct threats to employment prospects. This finding indicates that students may recognize continuous learning and reskilling as strategies for maintaining employability in the future labor market. This interpretation is consistent with previous research showing that AI-related skills are increasingly viewed as important resources for career development and employability enhancement rather than solely as sources of career concern (Deng & Sun, 2026; Portocarrero Ramos et al., 2025; Zhang et al., 2024).

Furthermore, this study demonstrates that career anxiety significantly mediates the relationship between AI-labor market transformation and career readiness, suggesting that students respond to AI-driven labor market uncertainty by becoming more motivated to prepare for their future careers. This finding is consistent with Testa et al. (2026), who found that career anxiety serves as an adaptive psychological mechanism that transforms concerns about AI-driven job displacement into proactive upskilling intentions among university students. However, career anxiety did not mediate the relationship between skill-based technological change and career readiness, indicating that changes in required skills may influence career preparation through other psychological mechanisms, such as AI readiness or career adaptability rather than anxiety (Testa et al., 2026).

The mediating role of career anxiety provides an important theoretical contribution by demonstrating that students' responses to AI are shaped not only by technological changes themselves but also by their psychological interpretations of those changes. Career anxiety, therefore, represents a bridge between perceived AI-driven labor market disruption and students' readiness to enter future employment. This finding expands previous research by showing that emotional responses to technological transformation play a central role in shaping career preparation behaviors (Jiang & Chen, 2026; Li et al., 2025).

In the Indonesian context, this study contributes to the limited empirical evidence regarding how AI-driven transformation influences university students' career-related perceptions. Previous studies in Indonesia have primarily examined digital transformation, workplace adaptation, and emerging skill requirements from organizational or workforce perspectives (Gayatri et al., 2022; Nugroho et al., 2024; Pertiwi, 2024; Winardi & Halim, 2024). However, limited attention has been given to the psychological mechanisms through which AI-related labor market changes influence students who are preparing to enter the workforce. By incorporating career anxiety as a mediating variable, this study extends existing Indonesian research by demonstrating that the impact of AI is not only related to technological adaptation but also involves psychological responses to uncertainty about future careers.

Overall, this study contributes to the growing literature on AI and career development by conceptualizing AI-driven job automation into two distinct dimensions: skill-based technological change and AI-labor market transformation. Unlike previous studies that often treat AI disruption as a single technological phenomenon, the present study demonstrates that these dimensions have different implications for university students' career psychology. The findings provide a more nuanced understanding of how AI influences career anxiety and career readiness, particularly in emerging economies where students are preparing to participate in rapidly changing labor markets.

4. CONCLUSION

This study examined the relationships among AI-labor market transformation, skill-based technological change, career anxiety, and career readiness among Indonesian university students. The findings reveal that AI-labor market transformation significantly increases career anxiety, whereas skill-based technological change does not significantly influence career anxiety. Furthermore, career anxiety positively influences career readiness and serves as a significant mediator between AI-labor market transformation and career readiness, indicating that students' psychological responses play an important role in translating AI-related labor market uncertainty into career preparation. In contrast, career anxiety does not mediate the relationship between skill-based technological change and career readiness, suggesting that changes in required skills may operate through other psychological mechanisms beyond anxiety.

Theoretically, this study contributes to the literature by distinguishing two dimensions of AI-driven change and AI-labor market transformation and skill-based technological change and demonstrating that they influence career development through different psychological pathways. Rather than viewing AI as a single source of disruption, the findings highlight that uncertainty regarding future employment opportunities has a stronger impact on students' career-related psychological responses than changes in skill requirements alone. Practically, the findings suggest that higher education institutions should not only strengthen AI literacy and digital competencies but also provide career guidance and psychological support to help students cope with uncertainty arising from AI-driven labor market transformation. Specifically, career development programs can provide AI-related career education, individualized career counseling, career planning activities, and resilience-building training to help students understand changing employment opportunities, manage career anxiety, and prepare for future labor market demands.

Despite the contributions, this study has several limitations. The cross-sectional design limits causal inference, and the sample was restricted to university students in Indonesia, which may limit the generalizability of the findings. Future research is encouraged to employ longitudinal or cross-cultural designs and to examine additional psychological mechanisms, such as career adaptability, career self-efficacy, AI readiness, or resilience, that may further explain how AI-related changes influence career readiness.

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