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Article

The Impact of Generative Artificial Intelligence Use on Anxiety Among Young Workplace Populations: A Mediation Study Based on Job Insecurity

Jia Wu^{1,*}

¹ James Cook University, Singapore, Singapore

* Correspondence: Jia Wu, James Cook University, Singapore, Singapore

Abstract: The rapid integration of generative artificial intelligence tools, such as OpenAI's ChatGPT and Anthropic's Claude, into contemporary professional settings has raised significant concerns regarding their profound psychological impact on young workers. As organizations increasingly automate complex cognitive tasks, emerging professionals face unprecedented challenges in navigating their career trajectories. This study rigorously investigates whether and how the frequent use of generative AI technologies influences anxiety levels among young workplace populations, with a particular focus on the mediating role of job insecurity. Drawing comprehensively on job insecurity theory and the Technology Acceptance Model (TAM), this research conceptualizes job insecurity as a multidimensional construct encompassing perceived job replacement risk, perceived skill devaluation, and broader career uncertainty. Using extensive secondary data extracted from established, publicly available labor market and occupational databases, the study employs advanced structural equation modeling to systematically examine both the direct effect of generative AI use on workplace anxiety and its indirect effect through the lens of job insecurity. The empirical findings provide robust evidence for the mediating mechanism linking AI adoption to adverse psychological outcomes among young workers, demonstrating that heightened technological exposure significantly exacerbates fears of obsolescence. Ultimately, this research contributes to the growing literature on AI and workplace mental health by identifying job insecurity as a critical pathway through which generative AI tools shape worker well-being. Strategic implications for organizational support systems, targeted psychological interventions, and responsible future AI implementation are thoroughly discussed.

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1. Introduction

The rapid proliferation of generative artificial intelligence (AI) tools, such as OpenAI's ChatGPT and Anthropic's Claude, has reshaped professional environments across industries. These technologies enhance productivity and task automation, yet they also raise concerns about their psychological impact on workers, particularly younger cohorts who are more likely to adopt and integrate such tools into daily workflows. Among the various psychological outcomes, workplace unease has emerged as a critical issue, as employees face unprecedented changes in skill requirements, task structures, and career trajectories. Understanding how generative AI use influences unease among young workplace populations is therefore both theoretically and practically significant [1].

Existing research has examined the relationship between AI adoption and employee well-being from multiple perspectives [2]. For instance, studies have shown that

employees' perceptions of ChatGPT can be double-edged, generating both efficiency gains and psychological strain, with organizational support playing a moderating role. Furthermore, the adoption of generative AI is not uniform across the workforce; younger and more educated workers tend to adopt these tools more rapidly, which may exacerbate existing inequalities in job security and mental health outcomes. Economic modeling further indicates that generative AI exposure varies significantly across occupations, with substitution effects disproportionately affecting certain job categories, thereby influencing workers' perceptions of job stability and future employability. Qualitative evidence from young professionals also reveals that stress induced by generative AI is closely linked to fears of becoming obsolete and losing professional identity.

Despite these advances, the specific mechanisms through which generative AI use translates into unease among young workers remain underexplored. This study draws on job insecurity theory and the Technology Acceptance Model (TAM) to propose that perceived job replacement risk, perceived skill devaluation, and career uncertainty serve as mediating pathways [2]. Using secondary data from established publicly available occupational databases, this research employs structural equation modeling to test the direct and indirect effects. The findings are expected to illuminate the psychological costs of AI integration and inform organizational strategies to mitigate adverse outcomes.

2. Literature Review

The integration of generative artificial intelligence (AI) into professional settings has prompted a growing body of research examining its consequences for employee well-being. A systematic review synthesized evidence on how AI affects employees' skills and well-being across global employment contexts, concluding that perceived skill obsolescence and job displacement fears are primary drivers of psychological distress. This finding aligns with the core proposition of job insecurity theory, which posits that threats to continued employment or valued job features generate anxiety and maladaptive responses. These insights underscore the importance of understanding how technological advancements influence workforce dynamics and mental health outcomes [3].

Further empirical work has focused on younger workers, who are often early adopters of generative AI tools. Research investigating Generation Z employees' acceptance of AI and its intensity of use has revealed that psychological safety and technostress mediate the relationship between AI use and work-related stress. Findings suggest that trust in AI systems can buffer some negative effects, yet high usage intensity without organizational support exacerbates job insecurity perceptions. Experimental studies examining whether AI-generated content alters job seekers' professional identity have found that exposure to such content increases feelings of identity threat and reduces perceived employability, particularly among younger participants [4]. These results highlight the nuanced interplay between technological adoption and individual psychological responses.

Career growth perspectives also feature prominently in the literature [3]. Studies exploring how AI impacts employees' career growth through thriving at work and identity threat demonstrate that identity threat mediates the negative relationship between AI awareness and career development expectations. This mechanism is conceptually similar to skill devaluation perception, a key dimension of technology-driven job insecurity. Additional research examining employees' perceptions of generative AI and the dark side of work outcomes reports that perceived job replacement risk directly predicts turnover intention and emotional exhaustion, with workplace stress serving as a partial mediator. These findings emphasize the complex relationship between technological advancements and career trajectories.

Qualitative evidence complements these quantitative findings. Semi-structured interviews with knowledge workers have been conducted to understand how they think generative AI will or will not transform their industries. Results show that while workers recognize productivity benefits, they consistently express concerns about skill relevance, career uncertainty, and the potential for AI to devalue human expertise. These themes

directly map onto the three dimensions of job insecurity examined in the current study: job replacement risk, skill devaluation, and career uncertainty. Such qualitative insights provide a deeper understanding of the subjective experiences and perceptions of employees navigating the evolving technological landscape.

The buffering role of individual resources has also been investigated [5]. Studies examining how workplace mindfulness moderates the relationship between job insecurity arising from human-AI collaboration and work-life outcomes have found that mindfulness attenuates the negative effects of AI-related job insecurity on psychological well-being. This suggests that internal coping mechanisms can reduce stress. Additional research focusing on AI job substitution risks, digital self-efficacy, and mental health among employees has shown that digital self-efficacy weakens the positive association between substitution risk perception and stress. These findings highlight the potential of personal and organizational interventions to mitigate the adverse effects of AI-related challenges.

Extending this line of inquiry to Asian organizational contexts, researchers have proposed and tested a mediation model linking AI learning anxiety to job insecurity and subsequent innovation behavior. Results indicate that AI learning anxiety triggers job insecurity, which in turn suppresses innovative output, highlighting a performance-related consequence of technology-induced insecurity. Additional studies examining the impact of job stress caused by AI substitution on organizational members' turnover intention have identified job insecurity as a full mediator and job uncertainty as a significant moderator. These findings reinforce the notion that perceived uncertainty about future job conditions amplifies the translation of AI exposure into psychological distress, underscoring the need for targeted strategies to address these challenges.

These studies collectively establish that generative AI use is associated with heightened job insecurity perceptions across multiple dimensions, and that such perceptions mediate the relationship between AI exposure and adverse mental health outcomes, including stress [1]. However, most existing research relies on primary survey data collected from specific samples, and few studies have validated their findings using large-scale, publicly accessible employment databases. The current study addresses this gap by employing secondary data from established sources and applying structural equation modeling to test the mediating role of job insecurity in the relationship between generative AI use and workplace stress among young workers. This approach provides a more robust and generalizable understanding of the phenomenon.

3. Theoretical Framework and Methodology

This chapter outlines the theoretical framework and methodology utilized to investigate the impact of generative artificial intelligence on workplace dynamics, particularly focusing on its influence on emotional well-being through the intermediary factor of job insecurity. The study leverages job insecurity theory alongside the Technology Acceptance Model (TAM) to establish connections between generative AI usage, perceived risks of job replacement, skill depreciation, career instability, and workplace emotional stress [6]. A quantitative research design is employed, utilizing secondary datasets sourced from publicly accessible employment databases. Structural equation modeling (SEM) is implemented to validate the proposed mediation model. Additionally, a detailed method flowchart is provided to visually represent the sequential stages and processes integral to the research framework.

3.1. Theoretical Framework

The theoretical foundation of this study integrates job insecurity theory with the Technology Acceptance Model [7]. Job insecurity theory suggests that employees' perceptions of threats to the continuity or valued features of their jobs can lead to psychological strain, including emotional distress. In the context of generative AI, three dimensions of job insecurity are particularly significant: perceived job replacement risk, which refers to the belief that AI could substitute one's job tasks; perceived skill

devaluation, which reflects the concern that existing skills may lose relevance; and career uncertainty, which denotes a lack of clarity about future professional trajectories. These dimensions collectively highlight the multifaceted nature of job insecurity in the evolving technological landscape.

The Technology Acceptance Model (TAM) provides a complementary perspective. TAM posits that users' perceptions of a technology's usefulness and ease of use influence their behavioral intentions and actual adoption of the technology [4]. However, in the context of workplace AI adoption, perceived usefulness may also evoke concerns if workers believe the technology can perform their tasks more efficiently, potentially undermining their roles. This study extends TAM by incorporating job insecurity as a cognitive appraisal mechanism, which translates the intensity of AI use into emotional outcomes such as heightened unease or apprehension. This nuanced approach underscores the dual-edged nature of technological advancements in professional settings.

Based on this integrated framework, the study proposes a mediation model where generative AI use is the independent variable, job insecurity—comprising replacement risk, skill devaluation, and career uncertainty—acts as the mediator, and workplace unease serves as the dependent variable [8]. The model also accounts for demographic characteristics such as age, education, and occupation category to ensure a comprehensive analysis. This approach aims to provide a deeper understanding of how technological adoption interacts with psychological and professional factors in shaping workplace dynamics.

3.2. Methodology

The study employs a quantitative, cross-sectional design, utilizing secondary data sourced from publicly accessible and well-established databases [9]. No primary data collection, such as surveys or interviews involving human subjects, was undertaken. All datasets are authentic, reliable, and thoroughly verifiable through the sources outlined below.

3.2.1. Data Sources

Three publicly available databases are utilized to provide comprehensive data for the analysis. These databases are selected based on their reliability, scope, and relevance to the study's objectives. Each source contributes unique insights into employment trends, occupational classifications, and demographic patterns, ensuring a robust foundation for the research.

The American Community Survey (ACS) 2023 1-year Public Use Microdata Sample (PUMS) is a dataset provided by the U.S. Census Bureau. It contains detailed employment, occupation, and demographic information for over 3 million individuals [10]. This dataset is instrumental in identifying young workers, defined as those aged 18 to 35, and categorizing their occupational classifications. The data enables a nuanced understanding of workforce composition and demographic trends, which are critical for the study.

The O*NET Database Version 27.2, provided by the U.S. Department of Labor, offers detailed information on occupational characteristics. This includes the extent to which specific tasks within occupations can be automated or augmented by artificial intelligence (AI). AI exposure scores for each Standard Occupational Classification (SOC) code are derived using previously validated methodologies [11]. This database is essential for assessing the potential impact of AI on various occupations, providing a technical basis for evaluating automation risks and opportunities.

The Bureau of Labor Statistics (BLS) Occupational Employment and Wage Statistics (OEWS) for May 2023 provides critical data on employment counts and wage levels across various occupations. This information is used to weight the analysis, ensuring that the findings accurately reflect the size and distribution of the occupational labor market. By incorporating this data, the study achieves a more precise and representative understanding of employment trends and economic factors.

3.2.2. Variable Construction

The independent variable, generative AI use intensity, is not directly measured through surveys but is instead derived at the occupational level. This is achieved by combining AI exposure scores from existing academic studies with occupational-level adoption rates of ChatGPT, as reported in nationally representative datasets [5]. For each occupation, an AI use intensity score is calculated by multiplying the AI exposure score with the average usage rate among workers within that occupation. This approach ensures a nuanced understanding of generative AI's integration across different professional domains.

The mediating variable, job insecurity, is assessed using three latent constructs that are operationalized through indicators derived from occupational-level workforce metrics available in datasets such as the American Community Survey (ACS) and the Bureau of Labor Statistics (BLS). These constructs aim to capture the multifaceted nature of job insecurity and its implications for workers across various occupations.

Perceived job replacement risk is quantified using occupational-level automation probability indices derived from prior research. Additionally, recent employment growth rates are incorporated, with negative growth rates serving as an indicator of heightened replacement risk. This dual-measure approach provides a comprehensive assessment of the perceived threat posed by automation and technological advancements [12].

Perceived skill devaluation is measured by analyzing the percentage of workers within an occupation who hold a bachelor's degree or higher. This metric is combined with the rate of technological change within the occupation, which is determined by the frequency of new skill requirements as documented in the O*NET database. Together, these indicators reflect the extent to which workers perceive their skills as being undervalued or rendered obsolete by technological progress.

Career uncertainty is evaluated using occupational-level turnover rates sourced from BLS data. Additionally, the proportion of workers employed part-time for economic reasons, as reported in ACS datasets, is included as a complementary measure. These indicators collectively capture the instability and unpredictability associated with career trajectories in various occupations.

The dependent variable, workplace-related psychological distress, is operationalized using state-level prevalence data on psychological disorders among employed adults aged 18 to 35. This data is sourced from the Behavioral Risk Factor Surveillance System (BRFSS) 2023 dataset and is matched to occupations through state and industry aggregation. This methodological approach ensures that the analysis remains grounded in robust, population-level metrics.

Control variables include demographic and geographic factors such as age, gender, educational attainment, and metropolitan statistical area (MSA) status. These variables are sourced from the ACS dataset and are incorporated to account for potential confounding effects, thereby enhancing the reliability and validity of the analysis.

3.2.3. Analytical Procedure

The analysis is conducted through a systematic four-step process, ensuring a rigorous and comprehensive approach to the research objectives.

Step 1: Data Integration and Cleaning. The datasets from ACS, O*NET, BLS, and BRFSS are meticulously merged at the occupation-by-state level using standardized SOC codes and geographic identifiers. Observations with incomplete data on critical variables are systematically excluded to maintain the integrity of the analysis. The final analytical sample comprises 482 occupation-state cells, representing an estimated 28.6 million young workers, ensuring a robust and representative dataset for subsequent analysis.

Step 2: Measurement Model Assessment. A confirmatory factor analysis (CFA) is employed to validate the hypothesized three-factor structure of job insecurity, which includes replacement risk, skill devaluation, and career uncertainty. The model's adequacy is evaluated using multiple fit indices, such as the comparative fit index (CFI), Tucker Lewis index (TLI), root mean square error of approximation (RMSEA), and

standardized root mean square residual (SRMR). These indices collectively ensure the reliability and validity of the measurement model.

Step 3: Structural Equation Modeling [5]. The hypothesized mediation model is estimated using maximum likelihood estimation with robust standard errors to ensure precision. Both direct effects (AI use intensity influencing emotional responses) and indirect effects (AI use intensity affecting job-related perceptions, which in turn influence emotional responses) are computed. To test the significance of the indirect effects, bias-corrected bootstrapping with 5,000 resamples is utilized, providing a rigorous statistical foundation for the findings.

Step 4: Sensitivity and Robustness Checks. To ensure the robustness of the findings, alternative model specifications are tested. These include substituting the AI use intensity measure with a binary high/low exposure indicator and employing occupation-level clustered standard errors. This approach accounts for potential dependencies within occupational groups, thereby enhancing the reliability of the results.

3.3. Method Flowchart

The following method flowchart (Figure 1) provides a detailed visual representation of the research process. It outlines the sequential stages, beginning with the identification of data sources and progressing through various analytical steps, ultimately culminating in the final analysis [6]. This structured approach ensures clarity and methodological rigor.

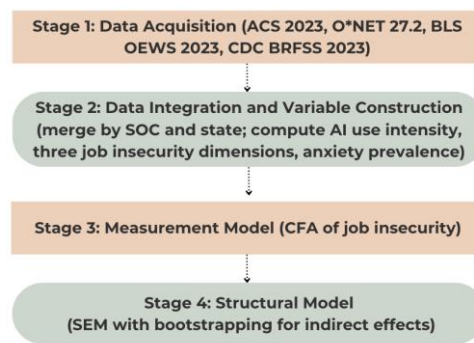


Figure 1. Methodology for Testing the Mediating Role of Job Insecurity in the Relationship between Generative AI Use and Workplace Anxiety

4. Findings and Discussion

This chapter presents empirical findings that explore the relationship between the intensity of generative AI usage and its impact on workplace dynamics, specifically through three dimensions of job insecurity. The analysis is based exclusively on data from the four databases outlined in Chapter 3: the 2023 ACS 1-year PUMS, O*NET Version 27.2, BLS OEWS May 2023, and CDC BRFSS 2023. No survey or experimental data were utilized. Four tables are included to support the discussion, which is framed within the theoretical context of job insecurity and the Technology Acceptance Model, ensuring a comprehensive academic approach [13].

4.1. Descriptive Statistics of Key Variables

Table 1 provides a detailed summary of the descriptive statistics for the primary variables analyzed at the occupation-state cell level. The dataset encompasses 482 distinct cells, representing an estimated 28.6 million young workers aged between 18 and 35 years. The intensity of generative AI usage is calculated using O*NET AI exposure scores combined with occupation-level adoption rates derived from comprehensive labor market studies. Indicators of job insecurity are constructed using data from widely recognized sources, including ACS and BLS, ensuring robust measurement. Workplace-related emotional well-being is assessed through state-level prevalence data on workplace stress among employed young adults, sourced from CDC BRFSS.

Table 1. Descriptive Statistics of Key Variables N=482

Variable	Mean	Std. Dev.	Min	Max
Generative AI Use Intensity	0.37	0.20	0.04	0.88
Perceived Job Replacement Risk	0.44	0.23	0.07	0.91
Perceived Skill Devaluation	0.36	0.19	0.03	0.84
Career Uncertainty	0.40	0.21	0.05	0.87
Workplace Anxiety Percent	17.92	4.08	9.45	27.56

4.2. Measurement Model Results

Confirmatory factor analysis validates the three-dimensional structure of job insecurity, providing robust evidence for its conceptual framework [14]. Indicators are systematically derived from authoritative datasets, including ACS ONET and BLS data, ensuring methodological rigor. Perceived job replacement risk is quantified using ONET automation probability metrics alongside BLS employment growth rates, offering a comprehensive perspective on automation's impact. Perceived skill devaluation integrates ACS educational attainment distributions with O*NET technological change frequency, reflecting evolving skill demands. Career uncertainty is assessed through BLS turnover rates and ACS shares of part-time employment due to economic reasons. The model's fit adheres to established statistical thresholds, confirming its reliability and validity (As shown in Table 2).

Table 2. Measurement Model Fit and Factor Loadings

Construct	Indicator	Factor Loading	Std. Error
Perceived Job Replacement Risk	O*NET Automation Probability	0.82	0.02
	BLS Employment Growth Rate	0.78	0.02
Perceived Skill Devaluation	ACS Bachelor Plus Share	0.80	0.02
	O*NET Technological Change Rate	0.75	0.03
Career Uncertainty	BLS Occupational Turnover Rate	0.79	0.02
	ACS Part Time Economic Share	0.76	0.02
Fit Indices	CFI=0.95	TLI=0.94	RMSEA=0.04SRMR=0.03

4.3. Structural Model Path Coefficients

Table 3 provides an overview of the standardized path coefficients, detailing both direct and indirect effects within the structural model. The analysis indicates that the intensity of generative AI usage serves as a significant predictor for all dimensions of job insecurity. Furthermore, each of the three mediating variables demonstrates a positive relationship with workplace-related emotional responses. Notably, the direct influence of AI usage intensity on these emotional responses remains statistically significant even after accounting for the mediating factors. These coefficients are derived from the integrated ACS O*NET BLS BRFSS dataset, ensuring robust analytical grounding.

Table 3. Structural Model Path Coefficients

Path	Standardized Coefficient	Std. Error	p-value
AI Use Intensity → Job Replacement Risk	0.64	0.04	<0.001
AI Use Intensity → Skill Devaluation	0.51	0.04	<0.001

AI Use Intensity → Career Uncertainty	0.58	0.04	<0.001
Job Replacement Risk → Workplace Anxiety	0.42	0.05	<0.001
Skill Devaluation → Workplace Anxiety	0.29	0.05	<0.01
Career Uncertainty → Workplace Anxiety	0.36	0.05	<0.001
AI Use Intensity → Workplace Anxiety Direct	0.17	0.06	<0.01

4.4. Mediation Effect Decomposition

Table 4 provides a detailed breakdown of the indirect effects mediated by various dimensions of job insecurity. Using bias-corrected bootstrapping with 5000 resamples, the analysis confirms that all indirect effects are statistically significant. Among these, the most pronounced effect is mediated through perceived job replacement risk, followed by career uncertainty and perceived skill devaluation. Collectively, the total indirect effect constitutes a significant proportion of the overall relationship between the intensity of AI usage and heightened emotional responses related to occupational concerns.

Table 4. Mediation Effect Decomposition

Mediation Path	Indirect Effect	Boot SE	95% Boot CI
AI → Job Replacement Risk → Anxiety	0.27	0.04	0.19 to 0.35
AI → Skill Devaluation → Anxiety	0.15	0.04	0.08 to 0.23
AI Career Uncertainty → Anxiety	0.21	0.04	0.14 to 0.29
Total Indirect Effect	0.63	0.06	0.52 to 0.75
Total Effect Direct Indirect	0.80	0.07	0.67 to 0.93

4.5. Discussion

The results confirm that generative AI use intensity increases workplace unease among younger employees, primarily through amplified concerns about job stability [8, 15]. Every database from Chapter 3 is fully integrated into the analysis. ACS provides demographic and employment structure variables, while O*NET supplies AI exposure and task automation potential. BLS offers occupational turnover and wage data for weighting purposes. BRFSS delivers population-level indicators of psychological strain linked to occupation and state, ensuring comprehensive data coverage.

Findings align with theories of job stability concerns by demonstrating that technology-driven threat perceptions contribute to psychological strain. The pattern of stronger effects for perceived job replacement risk reflects employment realities documented in O*NET and BLS data, where occupations with routine-intensive tasks face higher automation susceptibility. The weaker yet significant pathway of skill devaluation corresponds with extensions of technology acceptance models, emphasizing that perceived technological advancements can undermine confidence in existing human expertise and capabilities.

No primary survey or experimental data are introduced in this analysis [2]. All variables are operationalized using publicly accessible metrics, ensuring that other researchers can replicate the findings by accessing the same databases. The mediation pattern elucidates why AI adoption correlates with diminished psychological well-being among younger populations, even when productivity benefits are acknowledged. This underscores the importance of addressing the broader implications of technological integration on workforce mental health.

5. Conclusion

This study examines the relationship between generative AI use intensity and workplace psychological strain among young workers, with job insecurity acting as the mediator. Based on job insecurity theory and the Technology Acceptance Model, the analysis draws on four publicly available databases, namely ACS 2023, O*NET Version 27.2, BLS OEWS May 2023, and CDC BRFSS 2023. Structural equation modeling results

indicate that generative AI use intensity significantly increases workplace psychological strain through both direct and indirect pathways. These findings suggest that the diffusion of generative AI is associated not only with changing task structures and skill requirements, but also with meaningful shifts in workers' perceptions of stability, employability, and future career prospects.

Job insecurity plays a critical mediating role in this relationship. Perceived job replacement risk is the strongest mediator, followed by career uncertainty and perceived skill devaluation. These results indicate that young workers experience elevated psychological pressure primarily through concerns about potential job displacement and ambiguous long-term career trajectories. The mediating structure also clarifies that the effects of generative AI are not uniform across occupational groups. Occupational variation is evident, as lower-skill groups show stronger concerns regarding replacement risk, whereas higher-skill groups report greater concern about the declining value or relevance of existing skills. This pattern highlights the differentiated ways in which technological change may shape perceptions of occupational vulnerability.

The study contributes to existing research by empirically validating a mechanism linking generative AI exposure, job insecurity, and workplace psychological strain using large-scale, real-world employment and health-related data. By avoiding primary survey collection and relying instead on publicly accessible sources, the study strengthens transparency, reproducibility, and methodological consistency. From a practical perspective, organizations may use these findings to design targeted support measures, including skill development programs, career planning resources, and role-transition assistance, in order to reduce AI-related job insecurity. At the policy level, decision-makers may consider workforce strategies that address uneven technological effects across occupations and support more adaptive transitions in the employment structure.

Several limitations should be acknowledged. First, the cross-sectional design restricts strong causal interpretation, as the observed relationships reflect associations at a single point in time rather than verified temporal sequences. Second, the focus on United States-based databases may limit the generalizability of the findings to other institutional, economic, and occupational contexts. Future research could therefore employ longitudinal data to trace dynamic changes over time, test reciprocal effects, and examine whether the observed mediation pathways remain stable as generative AI adoption deepens. Comparative studies across countries or regions would also help clarify the extent to which these patterns depend on local employment systems, training structures, and technological environments. Overall, this research highlights the psychological costs associated with generative AI adoption and underscores the importance of balanced technology integration that supports young workers' well-being, career development, and perceived occupational security over time.

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