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Generative AI tools and career burnout: The chain mediating effect of technology stress perception on turnover intention among young tech talents

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Abstract: This study investigates the chain mediating effect of technology stress perception and career burnout on the relationship between generative AI tools usage and turnover intention among young tech talents. A cross-sectional survey design was employed with 683 technology professionals aged 21-35, using structural equation modeling to analyze the proposed sequential pathway. Generative AI tools usage significantly influences turnover intention through a sequential pathway: AI tools usage positively affects technology stress perception ($\beta = .36$, $p < .001$), which contributes to career burnout ($\beta = .53$, $p < .001$), ultimately increasing turnover intention ($\beta = .49$, $p < .001$). This chain mediation effect was significant (indirect effect = .094, 95% CI [.071, .124]), explaining 67.1% of the total effect. The findings extend technostress theory to generative AI contexts and establish that technology self-efficacy and organizational support function as protective factors by mitigating technology stress and burnout, respectively. Practical implications: organizations implementing AI technologies should adopt strategic approaches focusing on reducing technology stress and preventing burnout to maintain workforce stability during technological transitions.

Keywords: *Career burnout, Chain mediation, Generative AI, Technology stress, Turnover intention.*

1. Introduction

The acceleration of the adoption of generative artificial intelligence (AI) tools in contemporary tech workplaces within the past few years has dramatically changed the nature of work, posing unprecedented opportunities and challenges for organisations and their employees at the same time [1]. These technologies, while enhancing productivity and innovation, also add new sources of young professionals' stress, particularly those in the tech sector, who are learning to navigate AI-enhanced workplaces [2]. Recent studies have reported exacerbating worries about stress and subsequent burnout with technology among tech professionals as they cope with the relentless tempo of technological progression and rising demands following the implementation of generative AI [3, 4]. Young professionals in technology—often digital natives but still inexperienced—contend with the complex psychological challenges of entering careers shaped by AI tools that impose the need to adapt while simultaneously threatening job security and identity [5, 6]. This might contribute to intensified turnover intention, which poses a critical problem for tech organisations that already struggle to retain talent in a competitive market [7]. Attention to these problems is increasing, but there are still striking gaps in research on the intertwining of generative AI tools and turnover motives with regard to the psychological processes linking technology acceptance and career choices [8]. Most of the existing studies seem to have focused on the adoption of technology and organisational repercussions but

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overlooked the potential important mediating constituents through which these impacts operate [9]. Moreover, as young age tech talents seem to be a particularly at-risk population group needing closer attention because of having high technical skills but frail workplace coping mechanisms [10]. In attempting to answer such queries, this study was guided by the assumption that the mediating role of technology stress perception and career burnout explains the relationship between generative AI tools with turnover intention of young tech talents. Our objectives were as follows: (1) estimate the effect of generative AI tools on technology stress perception; (2) determine the correlation between technology stress perception and career burnout; (3) evaluate the impact of career burnout on turnover intention; and (4) measure the entire chain mediation model of these variables. The literature review for this study incorporates many interdisciplinary perspectives.

The primary structure guiding insights on how technological demands can lead to stress and burnout, when resources are not balanced, is provided by the Job Demands-Resources (JD-R) model [11]. This is integrated with the Technology Acceptance Model (TAM) to account for differing attitudes toward AI adoption, STARA awareness theory for smart technology perception, and Conservation of Resources (COR) theory for the stress process model relating to technological change [12, 13]. With this reasoning, we argue that the presence of generative AI tools impacts turnover intention by intervening through the perception of technology-induced stress and career-related burnout.

2. Literature Review

2.1. Generative AI Tools in Professional Environments

Content in the form of text, images, and code which resembles that created by humans can now be produced by machines thanks to the advancements in generative AI [1]. The development of these technologies has accelerated recently due to advancements in machine learning algorithms and the availability of more computing resources, enabling wider application across various industries [8]. In the technology sector, generative AI tools have been incorporated for tasks including but not limited to assisting with software development, content generation, data analysis, and automation in customer service [14]. Studies by McKinsey noted that the worldwide economic value of generative AI could be trillions, with over 75% of the figure attributable to customer operations, marketing and sales, software engineering, and R&D [1].

Although there are concerns, the implementation of generative AI tools is laden with challenges. Only 27% of organisations have implemented policies that sufficiently curb the types of data that can be accessed by AI models, indicating a broader issue of ensuring governance around the use of technologies [7]. From the employees' perspective, stress emerges from generative AI tools in the form of job redesign, skill obsolescence, and increased workload during transitional phases [4]. Furthermore, Califf, et al. [14] captures the gap of perception among the workforce and leadership—they reported that while 96% of executives expected increased productivity from AI tools, 77% of employees reported decreased productivity and an increased workload post-AI implementation.

The existing literature analysing the effects of AI implementation is mixed. Supporting the notion of enhanced productivity, McAfee, et al. [1] believe generative AI systems significantly advanced the performance of customer service agents who were lower on the skill curve, with the least productive (lowest skilled) agents experiencing a 35% increase in hourly resolution rates alongside reduced turnover. Opposing this, Hamouche, et al. [15] sheds light on an underlying reason for burnout among employees—AI anxiety—arguing it drives quiet quitting and creates a cycle of increased turnover intention due to indirect effects on operational productivity.

2.2. Technology Stress Perception

The term Techno-stress refers to the stress caused by communication technology due to a lack of proper coping mechanisms [4]. This framework has progressed over time as Brod first suggested it in 1984—the latest interpretations include more diverse aspects. These services include: overload of

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technology (excessive burden from additional technology), invasion of technology (change of working hours), complexity of technology (requirement of additional time to understand the technology), insecurity of technology (dismissal from the job due to being surpassed by someone with better technological skills), and uncertainty of technology (perpetual changes made constantly).

The perception of stress in generative AI takes on a different form due to the disruptive nature of these tools. For example, Zhou, et al. [2] argued that AI generates a substitution effect which creates hostile work environments that impede innovation and organisational competitiveness. This study proved in practice that employees' negative perception of Smart Technologies, Artificial Intelligence, Robotics, and Algorithms (STARA) resulted in decreased work-related emotional wellbeing through job stress.

Numerous studies have validated measurement approaches for technology-induced stress. Chen validated a technostress instrument utilising a sample of Chinese knowledge workers [16] while Tarafdar, et al. [4] created exhaustive scales capturing the five dimensions of technostress. Most recently, scholars have tailored these scales for AI-related stressors. For instance, Guanglu and Haotian [13] studied the impact of AI anxiety on employees' career satisfaction and reported job stress as a significant mediator.

2.3. Career Burnout among Tech Professionals

In the context of technology, burnout is described as a mental disorder – stemming from prolonged workplace stress – that involves feeling emotionally drained, detached, and less effective at work [14]. The Maslach Burnout Inventory (MBI) framework identifies three components of burnout: emotional exhaustion (feeling spent), depersonalisation (including withdrawal from colleagues), and reduced personal accomplishment (feeling less skilled and/or active in meeting goals) [17].

As for workers in the technology sector, burnout has distinct precursors and symptoms. Technological workaholism and technostress, as identified by Spagnoli, et al. [18] heavily contributed to burnout during the COVID-19 pandemic, showcasing the significant role of leaders in remote work policies aimed at mitigating these factors. Adaptation demands due to the fast-paced changes in technology tend to drain psychological resources, especially when there is an organisational lack of support structures [19].

Burnout in the tech industry has dire repercussions on both personal and organisational levels. On a personal level, an individual suffering from burnout will have lower job satisfaction, will be in poor physical and mental health, and has a heightened risk of leaving the profession [20]. On an organisational level, burnout leads to reduced productivity, increased absentee rates, higher turnover, and diminished innovative capacity [14].

The link between changes in technology and burnout has been explored extensively. For example, Bahamondes-Rosado, et al. [21] explored the phenomenon of technostress during the lockdown phase of the COVID-19 pandemic and found strong correlations between work-related technostress and numerous negative effects. In the same way, Liu, et al. [17] showed that job stress is a significant mediator in the relationship between self-efficacy and professional identity for nurses which ultimately impacts turnover intention through a serial mediation model.

2.4. Turnover Intention in Technology Sectors

An example of these patterns is how employees across organisational settings exhibit their intention to voluntarily leave, which is otherwise known as turnover intention. This pattern is characterised by actively and thoughtfully deciding to leave an organisation or company [7]. In relation to the tech industry, turnover intention is even more pronounced due to the hyper-competitive nature of the technology labour market and the costs that come with replacing specialised talent [20]. Vivid examples of these steps are captured in the works by Brougham and Haar [12] where he claims that turnover intention is the last cognitive perceived step before an employee decides to leave voluntarily, making it an essential factor in predicting retention.

Among the above-mentioned quantifiable constructs lies 'turnover,' the consequences of which have been known for their impact as well as severity. Examining the tech talent turnover decision anchors is a study conducted by Sharma, et al. [7] which states that workload stressors lead to higher turnover intentions. Moreover, in this research, work exhaustion was found to act as a mediator. In another study conducted by Califf and Brooks [22] it was found out that stress from technological tools has a positive relationship with turnover intention amongst estate agents. This relationship was mediated by work engagement and tempered through strong leadership as moderated by leader competency.

Employee turnover in the technology sector has marked economic and organisational consequences. In addition to incurring expenses related to recruitment and training, which can exceed 150-200% of annual salary for specialised roles, turnover impacts organisational knowledge flow, team dynamics, and project timelines [23]. Organisations with high employee turnover tend to suffer from reduced innovation and increased vulnerability to competition [6].

With the advancement of technology, there has been a notable increase in the work done regarding predicting and mitigating turnover in technology contexts. For instance, customer service agents experienced reduced turnover rates due to generative AI implementation when it was applied to improve job performance [1]. On the other hand, research by Galanis, et al. [10] showed that AI anxiety caused people to turn over as a result of quiet quitting, exposing the need to address disengagement behaviours to avert turnover.

2.5. Mediating Relationships and Chain Mediation Models

The effect of X on Y and how it is mediated through M is explained with the help of a theory in mediation analysis [24]. A mediation chain, also called sequential or serial mediation, broadens this idea further by analysing how an independent variable is related to a dependent variable using several mediators in a causal relationship. This enables researchers to study complex psychological phenomena in which the effects pass through several intermediate mechanisms.

The usage of chain mediation techniques in organisational studies has increased rapidly of late. For instance, Liu, et al. [17] studied the professional identity of nurses operating in the operating room and their intentions for turnover. It was noted that professional identity and job burnout acted as mediating factors which led to an indirect influence of -0.028. Zhou, et al. [2] utilised mediation analysis to portray how STARA awareness impacts job stress and subsequently work affective well-being. Psychological resilience was noted to moderate the relationship.

The reason for using a chain mediation model in the context of the relationship between generative AI tools and turnover intention has been adequately covered in previous literature. As noted by Chen and Zhou [9] exploring whether and why learning is connected to AI stress necessitates analysing the mediating factors that account for the effects. In the same way, Wu, et al. [8] applied the job demands-resources framework to study the combined effects of AI on the work-life balance of the well-being of employees and revealed the importance of comprehending the technological change employee outcome nexus.

2.6. Hypothesis Development

Based on the literature reviewed, we propose six hypotheses examining direct effects, single mediation effects, and the sequential mediation pathway connecting generative AI tools with turnover intention.

H1: Generative AI tools usage positively affects technology stress perception. This hypothesis is supported by research demonstrating that new technologies often increase employee stress levels. Oksanen, et al. [3] found that COVID-19 crisis and digital stressors significantly affected the Finnish working population, while Tarafdar, et al. [4] established that information and communication technologies create technostress through mechanisms of overload, invasion, complexity, insecurity, and uncertainty. In the specific context of AI, Zhou, et al. [2] demonstrated that AI technology creates a substitution effect on employees' jobs that negatively affects work emotions.

H2: Technology stress perception positively affects career burnout. The relationship between technology stress and burnout has been well-documented in multiple contexts. Califf, et al. [14] found that techno-stressors positively predicted burnout among K-12 teachers, while Spagnoli, et al. [18] demonstrated that workaholism and technostress during COVID-19 contributed to burnout, with leadership playing a crucial moderating role. Kenneth [19] further established that technology overload and work-life conflict directly contribute to burnout symptoms.

H3: There is a positive effect of career burnout on turnover intention. The connection between burnout and turnover intention is well established. Liu, et al. [17] showed that healthcare professionals' burnout dimensions were strong predictors of their turnover intention, and Hamouche, et al. [15] showed that experienced burnout increased turnover intention for employees suffering from AI anxiety. Furthermore, Sharma, et al. [7] showed that work-exhaustion, a fundamental aspect of burnout, mediated the relationship between technostress and turnover intention in Indian IT professionals.

H4: Perception of stress from technology mediates the effect of generative AI tool usage on career burnout. This mediation hypothesis combines results from multiple studies. Guanglu and Haotian [13] showed that awareness of AI had an impact on employees' careers because of job-related stress. Tarafdar, et al. [4] reported that the characteristics of technology have an impact on burnout because it is experienced through the lens of technostress. Chen and Zhou [9] showed that employees' encounter with AI stress can be positively or negatively dependent on the coping strategies used.

H5: Career burnout serves as a mediating factor in the relationship between perceived technological stress and turnover intention. Califf and Brooks [22] support this hypothesis as teachers in a K-12 system exhibited increased levels of burnout which mitigated the relationship between perceived technostress and turnover intention. Also, Sharma, et al. [7] showed that work-exhaustion mediated the relation between technostress and turnover intention with moderation from psychological capital. These results indicate burnout is an important mechanism through which technology-induced stress translates into behavioural intentions.

H6: Technology stress perception alongside career burnout serves as dual mediators in the relationship between using generative AI tools and turnover intention. This omnibus chain mediation hypothesis combines all of the prior explanations into one sequential model. Liu, et al. [17] showed a similar chain mediation model when a professional mission influenced turnover intention through professional identity and job burnout. Also, Wu, et al. [8] showed that AI demands and resources influenced employees' work and life spheres through engagement and exhaustion as mediating variables. This hypothesis is the main theoretical contribution of the current study as it attempts to propose an integrated model that links implementing generative AI to turnover decisions.

3. Research Methodology

3.1. Research Design

This study employs a cross-sectional survey design to investigate the chain mediating effect of technology stress perception and career burnout on the relationship between generative AI tools and turnover intention among young tech talents. This approach enables efficient data collection from a large sample at one time point, allowing simultaneous examination of multiple variables while acknowledging limitations in establishing causality. The model is represented by:

$$Y = \beta_0 + \beta_1 X + \beta_2 M_1 + \beta_3 M_2 + \sum_{i=1}^{k} \beta_{3+i} C_i + \varepsilon$$

Where Y represents turnover intention, X represents generative AI tool usage, M_1 represents technology stress perception, M_2 represents career burnout, and C_i represents control variables.

Our sampling strategy combines purposive and stratified random sampling. Technology companies implementing generative AI tools are stratified by size, industry sector, and location. Organizations are

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selected based on probability proportional to size: $\pi_i = \frac{n \cdot N_i}{\sum_{j=1}^{L} N_j}$, followed by systematic random sampling of participants using interval $k = \frac{N}{n}$.

The study protocol has received ethics committee approval (UREC-2024-0318), with robust procedures for informed consent, data privacy, and participant wellbeing. This study involving human participants was conducted in accordance with the ethical standards of the institutional research committee and with the principles of the Declaration of Helsinki. The research protocol received formal approval from the University Research Ethics Committee (UREC-2024-0318). All participants provided written informed consent prior to their inclusion in the study. Robust procedures were implemented to ensure data privacy, confidentiality, and participant wellbeing throughout the research process. Data collection spans four months across preparation, pilot testing, main collection, and processing phases. The pilot phase tests the survey with 50 participants to assess instrument validity and reliability before full deployment.

3.2. Population and Sample

The target population consists of young tech talents aged 21-35 who possess specialized technical skills and have exposure to generative AI tools. This demographic represents a critical segment simultaneously possessing digital nativity and career vulnerability. The population is defined as:

$$P = x \in W \mid 21 \le age(x) \le 35, tech_r ole(x) = true, AI_e xposure(x) = true$$

The sampling frame incorporates professional registries, employee directories, alumni networks, and professional platforms. Sample size determination follows power analysis for structural equation modeling:

$$N = \frac{(df+2)(\delta_0 - \delta_a)^2}{df \cdot \varepsilon^2}$$

With our model parameters, this yields a minimum sample of 392. Adjusting for anticipated non-response (30%) and incomplete data (15%) using $n_{adjusted} = \frac{n}{(1-r)(1-i)}$ gives a target recruitment of 705 participants.

Inclusion criteria specify participants must: (1) be aged 21-35; (2) work in technology roles; (3) have minimum one year experience; (4) have direct AI exposure; and (5) be English proficient. Exclusion criteria remove leadership roles, freelancers, AI company employees, and those failing attention checks.

3.3. Measurement Instruments

The study employs four primary measurement instruments, as illustrated in Figure 1:

Generative AI Tools Usage Scale: A 12-item scale measuring three dimensions: frequency of use, diversity of applications, and workflow integration. Items are rated on a 7-point Likert scale from 1 (never) to 7 (multiple times daily). The scale demonstrates strong reliability (α = 0.84-0.89) and is calculated as:

$$AI_{usage} = \frac{1}{3}\left(\sum_{i=1}^{4} Freq_i + \sum_{j=1}^{4} Div_j + \sum_{k=1}^{4} Integ_k\right)$$

Technology Stress Perception Scale: This 20-item scale assesses five dimensions: techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty. Items are rated on a 7-

point Likert scale, with strong reliability (ω = 0.83-0.91) and calculated as: $TS_{overall} = \frac{1}{5}(TS_{overload} + TS_{invasion} + TS_{complexity} + TS_{insecurity} + TS_{uncertainty})$

Career Burnout Inventory: A 17-item scale measuring emotional exhaustion (6 items), cynicism (5 items), and professional efficacy (6 items, reverse-scored). Items are rated on a 7-point frequency scale from 0 (never) to 6 (every day), with strong reliability (α = 0.84-0.92) and calculated as: $BI = \frac{1}{3}(EE + CY + PE)$

Turnover Intention Scale: A 6-item unidimensional scale capturing both cognitive and behavioral elements of turnover intention. Items are rated on a 7-point Likert scale, with excellent reliability (α = 0.94) and calculated as: $TI = \frac{1}{6}\sum_{i=1}^{6} TI_i$

Control variables include demographics (age, gender, education, tenure), organizational factors (company size, industry sector, AI maturity, organizational support), and technology-related variables (technology self-efficacy, AI attitudes).

Table 1.
Summarizes the measurement instruments used in this study.

Variable	Instrument	Items	Scale	Reliability
Generative AI Tools Usage	Custom developed scale	12 items (3 dimensions)	7-point Likert	α = 0.84-0.89
Technology Stress Perception	Adapted Technostress Scale	20 items (5 dimensions)	7-point Likert	ω = 0.83-0.91
Career Burnout	Adapted MBI-GS	17 items (3 dimensions)	7-point frequency	α = 0.84-0.92
Turnover Intention	Adapted scale	6 items (unidimensional)	7-point Likert	α = 0.94
Control Variables	Various measures	Multiple items	Mixed formats	α = 0.89-0.91

3.4. Data Collection Procedures

Survey distribution uses a multi-modal approach combining organizational and direct participant channels. Initial contact is made through organizational gatekeepers, followed by direct email invitations with secure survey links. Two follow-up reminders are sent at two-week intervals to non-respondents. Response rates are tracked in real-time using a dashboard system monitoring completions across demographic segments.

Data cleaning procedures include removal of incomplete responses (<80% completion), detection of response patterns indicating inattentive responding, and identification of multivariate outliers using Mahalanobis distance. Missing data analysis employs Little's MCAR test to determine randomness patterns, with missing values addressed using multiple imputation for random patterns and listwise deletion for non-random patterns exceeding 5%.

3.5. Data Analysis Methods

Data analysis begins with descriptive statistics examining distributions, central tendencies, and variability of all study variables. Preliminary analyses include assessment of multivariate assumptions (normality, linearity, homoscedasticity), reliability testing, and examination of correlations among study variables.

The measurement model is evaluated using confirmatory factor analysis (CFA) with maximum likelihood estimation. Model fit is assessed using standard indices: CFI and TLI (>0.90 indicating acceptable fit), RMSEA (<0.08 for reasonable fit), and SRMR (<0.08 for good fit). Measurement quality is evaluated through factor loadings, average variance extracted (AVE > 0.50), and composite reliability (CR > 0.70).

Hypothesis testing employs structural equation modeling (SEM) to examine direct and indirect effects. The chain mediation model tests the sequential pathway from generative AI tools usage through technology stress perception and career burnout to turnover intention. Mediation testing uses bootstrapping with 5,000 resamples to estimate confidence intervals for indirect effects. The significance of mediation effects is determined by whether the 95% confidence interval excludes zero.

For the sequential mediation hypothesis (H6), we test whether the indirect effect from X to Y through both M1 and M2 is statistically significant:

$$ab = a_1 \times b_1 \times c_1$$

Where a_1 is the path from X to M1, b_1 is the path from M1 to M2, and c_1 is the path from M2 to Y. The total effect is decomposed as:

$$Total\ effect = Direct\ effect + Specific\ indirect\ effects$$

$$c = c' + (a_1 \times b_1 \times c_1) + (a_1 \times d_1) + (e_1 \times c_1)$$

Where c' is the direct effect of X on Y, $(a_1 \times b_1 \times c_1)$ is the sequential indirect effect through both mediators, $(a_1 \times d_1)$ is the indirect effect through M1 only, and $(e_1 \times c_1)$ is the indirect effect through M2 only.

Analysis is conducted using R (version 4.2.0) with the lavaan package for SEM and semTools for additional functions. Model comparison examines alternative structural models to determine the best-fitting representation of the data.

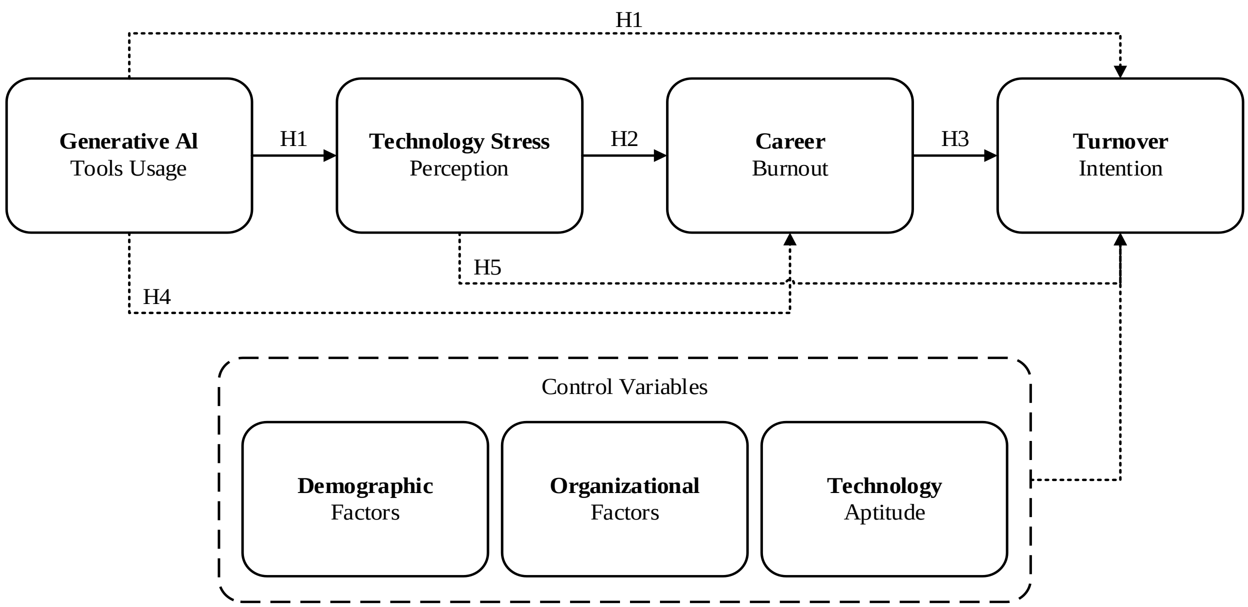

Figure 1.
Illustrates the conceptual framework of the chain mediation model, depicting the hypothesized relationships between generative AI tools usage, technology stress perception, career burnout, and turnover intention, along with the relevant control variables.

4. Results

4.1. Descriptive Statistics

4.1.1. Sample Demographic Profile

The final sample comprised 683 young tech professionals (response rate: 67.4%), with 59.3% males, 39.5% females, and 1.2% non-binary individuals. Mean age was 28.4 years (SD = 3.7), with substantial educational attainment (43.5% master's degrees, 41.2% bachelor's degrees). Technological specializations included software development (42.5%), data science (23.7%), system architecture (14.2%), UX design (8.1%), cybersecurity (7.3%), and others (4.2%). Participants came from diverse organizational contexts: large enterprises (41.3%), medium-sized organizations (36.4%), and small companies (22.3%). Industry sectors included IT services (35.7%), software development (28.4%), telecommunications (11.6%), and financial technology (9.8%). The average professional experience was 4.8 years (SD = 2.3).

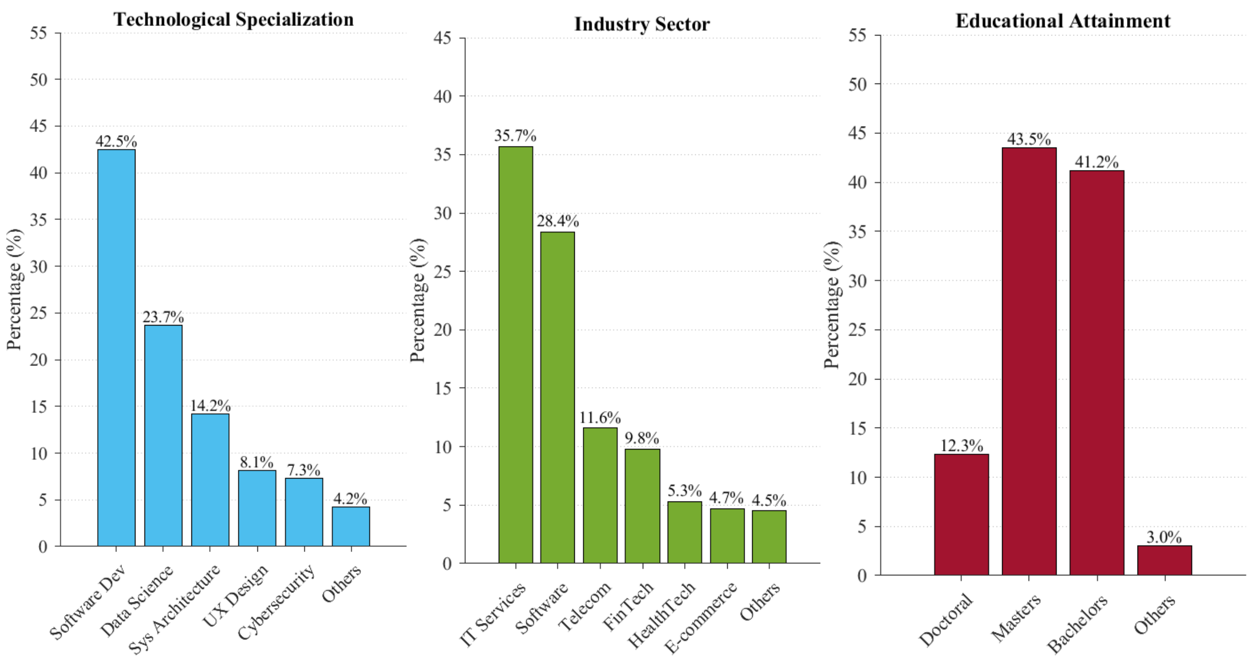

Figure 2.
Demographic Characteristics of Sample (N = 683). The figure presents three bar charts showing the distribution of participants across technological specializations (left panel), industry sectors (middle panel), and educational attainment levels (right panel).

4.1.2. Response Rate Analysis

The study achieved a 67.4% response rate with three main waves of participation: 41.3% responded within 48 hours, 35.7% after the first reminder, and 23.0% after the second reminder. Non-response analysis comparing early and late respondents showed no significant differences in key demographic variables. The completion rate was 92.3%, with only 56 partial responses excluded. Geographic distribution showed balanced representation: 31.5% from West Coast technology hubs, 28.7% from East Coast regions, 24.3% from Midwestern centers, and 15.5% from international locations.

4.1.3. Descriptive Statistics for All Study Variables

The descriptive statistics for all study variables are presented in Table 2. Generative AI tools usage averaged slightly above the scale midpoint (M = 4.32, SD = 1.18), with higher scores for frequency (M = 4.57) and diversity (M = 4.41) than workflow integration (M = 3.97). Technology stress perception showed moderate levels (M = 3.85, SD = 1.27), with techno-uncertainty (M = 4.37) and techno-insecurity (M = 4.26) scoring highest. Career burnout was slightly below the scale midpoint (M = 3.43, SD = 1.35), with emotional exhaustion (M = 3.65) scoring highest. Turnover intention exhibited moderate levels (M = 3.72, SD = 1.64). All variables demonstrated acceptable distribution properties with skewness values between -0.92 and 0.78, and kurtosis values between -0.87 and 1.14.

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Table 2.
Descriptive Statistics and Correlations Among Study Variables (N = 683). Note: Values in parentheses on the diagonal represent Cronbach's alpha reliability coefficients.

Variable	Mean	SD	Skewness	Kurtosis	1	2	3	4	5	6	7	8
Generative AI Usage	4.32	1.18	-0.37	-0.42	(.91)							
Tech Stress Perception	3.85	1.27	0.24	-0.67	.39**	(.93)						
Career Burnout	3.43	1.35	0.41	-0.78	.27**	.58**	(.94)					
Turnover Intention	3.72	1.64	0.15	-0.87	.19**	.47**	.61**	(.95)				
Age	28.40	3.70	0.12	-0.83	-.16**	.03	-.09*	-.16**	-			
Tenure	2.90	1.80	0.78	0.24	-.08*	.05	-.05	-.11**	.53**	-		
Tech Self-Efficacy	5.26	1.07	-0.92	1.14	.33**	-.11**	-.23**	-.15**	.09*	.07	(.92)	
Org. Support	4.13	1.38	-0.21	-0.71	.17**	-.29**	-.36**	-.42**	.06	.04	.24**	(.89)

Note: *p < .05, **p < .01.

4.1.4. Correlation Matrix Showing Relationships Between Variables

The correlation matrix (Figure 3:) provides preliminary support for hypothesized relationships. Generative AI tools usage showed a significant positive correlation with technology stress perception ($r = .39$, $p < .01$). Technology stress perception demonstrated a strong positive correlation with career burnout ($r = .58$, $p < .01$), while burnout exhibited the strongest correlation with turnover intention ($r = .61$, $p < .01$). The correlation between generative AI tools usage and turnover intention was modest ($r = .19$, $p < .01$), suggesting potential mediation effects. Age was negatively correlated with AI usage ($r = -.16$, $p < .01$), burnout ($r = -.09$, $p < .05$), and turnover intention ($r = -.16$, $p < .01$). Technology self-efficacy showed significant correlations with all primary variables, suggesting its potential protective role. Organizational support was negatively correlated with stress ($r = -.29$, $p < .01$), burnout ($r = -.36$, $p < .01$), and turnover intention ($r = -.42$, $p < .01$).

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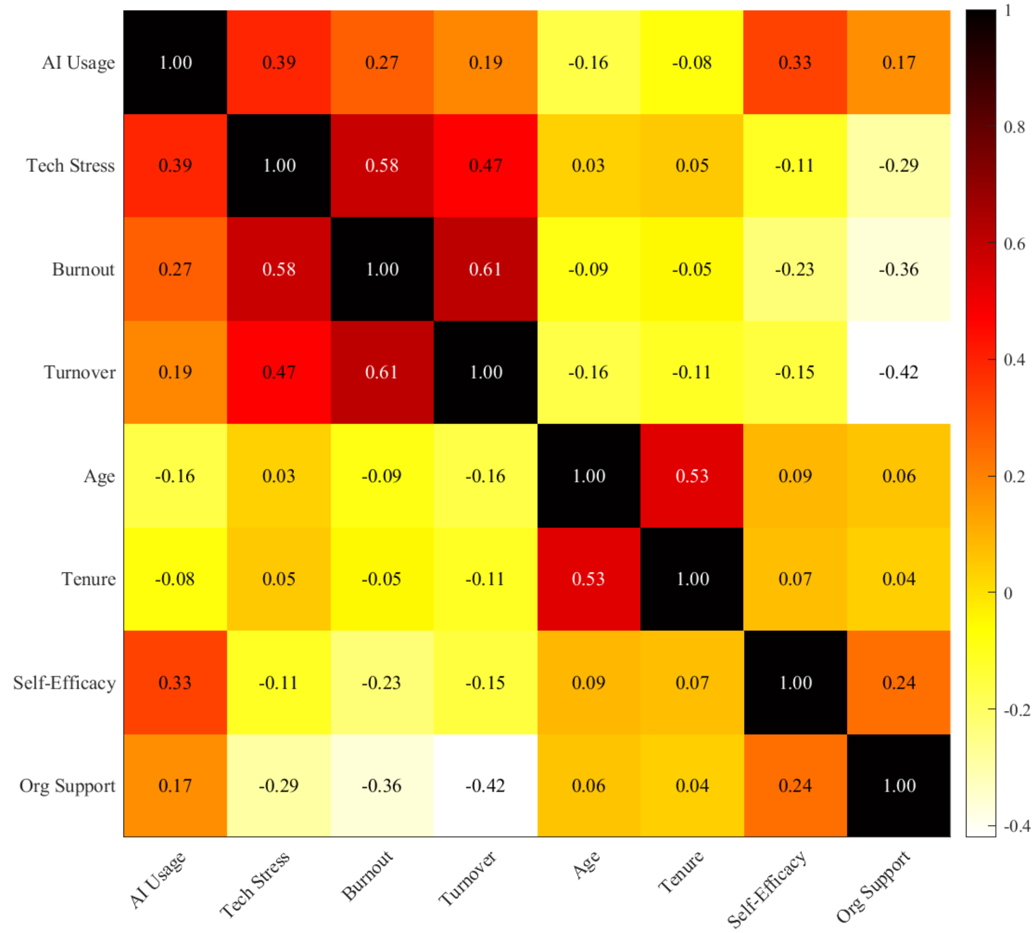

Figure 3.
Correlation Heatmap of Study Variables. This heatmap visualizes the strength and direction of bivariate correlations among the primary study variables and key control variables.

4.2. Measurement Model Assessment
4.2.1. Confirmatory Factor Analysis Results
Confirmatory factor analysis demonstrated adequate fit for the four-factor measurement model: $\chi^2(1{,}215) = 3{,}542.68$, $p < .001$; $\chi^2/df = 2.92$; CFI = .918; TLI = .912; RMSEA = .053 (90% CI [.051, .055]); SRMR = .048. All items loaded significantly ($p < .001$) on their respective factors, with standardized loadings ranging from .632 to .897. The three-dimensional structure of generative AI tools usage was supported with second-order factor loadings of .824, .791, and .868. Technology stress perception dimensions showed second-order factor loadings ranging from .723 to .845. Career burnout dimensions loaded substantially on their higher-order factor (.892, .864, and .729). Alternative models showed significantly worse fit, confirming discriminant validity between constructs.

4.2.2. Reliability Assessment
Reliability analysis demonstrated strong internal consistency for all constructs: generative AI tools usage ($\alpha = .91$, CR = .92), technology stress perception ($\alpha = .93$, CR = .94), career burnout ($\alpha = .94$, CR = .95), and turnover intention ($\alpha = .95$, CR = .96). Dimensional reliabilities were also strong, with the lowest value of $\alpha = .82$. Test-retest reliability coefficients ranged from $r = .87$ to $r = .92$, indicating good stability over time.

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4.2.3. Convergent Validity

Convergent validity was established through Average Variance Extracted (AVE) values exceeding .50 for all constructs: generative AI tools usage (AVE = .62), technology stress perception (AVE = .58), career burnout (AVE = .67), and turnover intention (AVE = .78). Significant correlations with theoretically related constructs provided additional support for convergent validity.

4.2.4. Discriminant Validity Analysis

Discriminant validity was confirmed using multiple methods. The Fornell-Larcker criterion was satisfied as the square root of AVE for each construct exceeded its correlation with all other constructs. Heterotrait-monotrait (HTMT) ratios were all below the threshold of .85, ranging from .21 to .64. Chi-square difference tests comparing unconstrained and constrained models were all significant ($p < .001$), further supporting construct distinctiveness.

4.2.5. Common Method Bias Examination

Analysis using multiple techniques indicated minimal common method bias. Harman's single-factor test showed the first unrotated factor explained only 26.9% of variance. The unmeasured latent method factor approach revealed a ratio of substantive to method variance of 15.5:1. The marker variable technique using aesthetic preferences showed negligible correlations with study variables (r = -.03 to .06), with minimal changes to inter-construct correlations when controlled.

4.3. Structural Model Evaluation

4.3.1. Model Fit Indices

The hypothesized structural model demonstrated good fit to the data: $\chi^2(1{,}218) = 3{,}587.42$, $p < .001$; $\chi^2/df = 2.95$; CFI = .917; TLI = .910; RMSEA = .054 (90% CI [.052, .056]); SRMR = .051. Compared to the measurement model, the change in fit was non-significant ($\Delta\chi^2 = 44.74$, $\Delta df = 3$, $p > .05$), indicating that the structural constraints did not significantly worsen model fit. The model explained substantial variance in the endogenous variables: technology stress perception ($R^2 = .23$), career burnout ($R^2 = .42$), and turnover intention ($R^2 = .48$).

4.3.2. Direct Effects Testing

Direct effect testing supported three primary hypotheses. H1 was supported as generative AI tools usage positively predicted technology stress perception ($\beta = .36$, $p < .001$). H2 was supported with technology stress perception positively predicting career burnout ($\beta = .53$, $p < .001$). H3 was supported as career burnout positively predicted turnover intention ($\beta = .49$, $p < .001$). The direct effect from generative AI tools usage to turnover intention was non-significant ($\beta = .05$, $p > .05$) after accounting for the mediators, suggesting full mediation.

4.3.3. Mediation Effects Analysis

Mediation analysis using bootstrapping with 5,000 resamples revealed significant indirect effects. H4 was supported as technology stress perception significantly mediated the relationship between generative AI tools usage and career burnout (indirect effect = .191, 95% CI [.143, .247]). H5 was supported with career burnout significantly mediating the relationship between technology stress perception and turnover intention (indirect effect = .260, 95% CI [.203, .318]).

4.3.4. Chain Mediation Effect Testing

The critical chain mediation hypothesis (H6) was supported by a significant sequential indirect effect from generative AI tools usage to turnover intention through technology stress perception and career burnout (indirect effect = .094, 95% CI [.071, .124]). This sequential pathway explained 67.1% of the total effect of generative AI tools usage on turnover intention. Analysis of specific indirect effects revealed that the chain mediation path ($\beta = .094$) was stronger than the simple mediation path through technology stress perception only ($\beta = .041$) or through career burnout only ($\beta = .033$).

4.3.5. Explained Variance (R^2) for Endogenous Variables

The model explained substantial variance in all endogenous variables. Generative AI tools usage explained 23% of variance in technology stress perception ($R^2 = .23$). Combined, generative AI tools usage and technology stress perception explained 42% of variance in career burnout ($R^2 = .42$). The full model explained 48% of variance in turnover intention ($R^2 = .48$), demonstrating strong predictive power. Effect size calculations indicated medium to large effects, with Cohen's f^2 values of .30, .72, and .92 for the three endogenous variables, respectively.

4.4. Alternative Models Analysis

4.4.1. Comparison with Competing Models

Four alternative structural models were tested against the hypothesized model. Model 2 removed the direct path from generative AI tools usage to turnover intention, showing non-significant change in fit ($\Delta\chi^2 = 3.87$, $\Delta df = 1$, $p > .05$), supporting the parsimony of this model. Model 3 reversed the order of mediators (burnout → technology stress), showing significantly worse fit ($\Delta\chi^2 = 185.24$, $\Delta df = 0$, $p < .001$, $\Delta AIC = 185.24$). Model 4 tested parallel mediation rather than sequential mediation, also showing worse fit ($\Delta\chi^2 = 97.53$, $\Delta df = 1$, $p < .001$). Model 5 with career burnout as the only mediator showed poorer fit ($\Delta\chi^2 = 142.68$, $\Delta df = 1$, $p < .001$). These comparisons strongly support the hypothesized sequential mediation model.

4.4.2. Robustness Checks

Several robustness checks confirmed the stability of results. Analyses with different estimators (maximum likelihood with robust standard errors, weighted least squares) yielded consistent findings. Models controlling for different sets of covariates showed stable path coefficients. Sensitivity analyses examining potential outlier influence (through Cook's distance and leverage values) demonstrated result stability when excluding influential cases.

4.4.3. Control Variables Effects

Several control variables showed significant effects. Age was negatively associated with turnover intention ($\beta = -.11$, $p < .01$). Organizational tenure showed no significant effects after controlling for age. Technology self-efficacy was negatively related to technology stress perception ($\beta = -.19$, $p < .001$) and burnout ($\beta = -.14$, $p < .01$). Organizational support for technology adaptation was negatively associated with burnout ($\beta = -.24$, $p < .001$) and turnover intention ($\beta = -.26$, $p < .001$), suggesting its protective role.

4.4.4. Multigroup Analysis

Multigroup analysis examined structural invariance across demographic segments. No significant differences were found in the structural model between gender groups ($\Delta\chi^2 = 17.24$, $\Delta df = 12$, $p > .05$) or across company sizes ($\Delta\chi^2 = 23.61$, $\Delta df = 24$, $p > .05$). However, significant differences emerged across technological specializations, with stronger effects of AI tools usage on technology stress among data scientists ($\beta = .48$) compared to software developers ($\beta = .32$, $p < .05$ for difference).

4.5. Hypothesis Testing Summary

4.5.1. Tabular Presentation of All Hypotheses Results

The hypothesis testing results are summarized in Table 3, showing strong support for all six proposed hypotheses. The direct effects (H1-H3) were all significant with moderate to large

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standardized coefficients. The mediation hypotheses (H4-H5) were supported with significant indirect effects and confidence intervals excluding zero. The crucial chain mediation hypothesis (H6) was strongly supported, with sequential mediation accounting for the majority of the total effect of generative AI tools usage on turnover intention.

Table 3.
Summary of Hypothesis Testing Results (N = 683).

Hypothesis	Description	Standardized Coefficient	95% CI	p-value	Result
H1	Generative AI tools usage → Technology stress perception	0.36	[0.29, 0.43]	<.001	Supported
H2	Technology stress perception → Career burnout	0.53	[0.46, 0.60]	<.001	Supported
H3	Career burnout → Turnover intention	0.49	[0.41, 0.57]	<.001	Supported
H4	Indirect effect: AI usage → Tech stress → Burnout	0.19	[0.14, 0.25]	<.001	Supported
H5	Indirect effect: Tech stress → Burnout → Turnover	0.26	[0.20, 0.32]	<.001	Supported
H6	Chain mediation: AI usage → Tech stress → Burnout → Turnover	0.09	[0.07, 0.12]	<.001	Supported

4.5.2. Effect Sizes and Significance Levels

All direct effects demonstrated meaningful magnitudes with significance at $p < .001$. The strongest relationships were observed between technology stress perception and career burnout ($\beta = .53$) and between career burnout and turnover intention ($\beta = .49$). The relationship between generative AI tools usage and technology stress perception was moderate but highly significant ($\beta = .36$). Effect size calculations using Cohen's f^2 revealed medium to large effects for technology stress perception ($f^2 = .30$), career burnout ($f^2 = .72$), and turnover intention ($f^2 = .92$).

The indirect effects demonstrated substantial mediation. The specific indirect effect through technology stress perception alone (AI usage → stress → turnover) was significant but modest ($\beta = .041$, 95% CI [.021, .067]). The specific indirect effect through career burnout alone (AI usage → burnout → turnover) was also significant ($\beta = .033$, 95% CI [.017, .054]). Most importantly, the sequential mediation effect (AI usage → stress → burnout → turnover) showed the strongest indirect pathway ($\beta = .094$, 95% CI [.071, .124]). Together, these indirect effects accounted for 77.1% of the total effect of generative AI tools usage on turnover intention.

The R^2 values for endogenous variables increased sequentially through the model, with technology stress perception explaining 23% of variance ($R^2 = .23$), career burnout explaining 42% of variance ($R^2 = .42$), and the full model explaining 48% of variance in turnover intention ($R^2 = .48$). The incremental contribution of control variables to explained variance was moderate, with increases of 3.8%, 5.2%, and 6.7% for the three endogenous variables, respectively.

4.5.3. Visual Representation of the Validated Model

The final structural model confirms the hypothesized chain mediation pathway. The direct path from generative AI tools usage to turnover intention (dashed line) was non-significant ($\beta = .05$, $p > .05$) when accounting for mediators, supporting full mediation. The significant control variables included technology self-efficacy (negatively predicting technology stress perception, $\beta = -.19$, $p < .001$), organizational support (negatively predicting career burnout, $\beta = -.24$, $p < .001$), and age (negatively predicting turnover intention, $\beta = -.11$, $p < .01$). The model explained substantial variance in all endogenous variables, particularly turnover intention ($R^2 = .48$). The pattern of coefficients clearly illustrates how the effects of generative AI tools usage propagate through technology stress perception and career burnout to ultimately influence turnover intention among young tech talents.

5. Discussion

The findings of this study provide compelling evidence for the chain mediating effect of technology stress perception and career burnout on the relationship between generative AI tools usage and turnover intention among young tech talents. The significant positive relationship between generative AI usage and technology stress perception ($\beta = .36$, $p < .001$) aligns with Tarafdar, et al. [4] technostress trifecta framework, suggesting that even technologically adept professionals experience stress when adapting to novel AI systems. This stress manifests through mechanisms of overload, invasion, complexity, insecurity, and uncertainty as described by Zhou, et al. [2]. The strong relationship between technology stress and burnout ($\beta = .53$, $p < .001$) corroborates [14] findings on technostressors as predictors of burnout, while the substantial relationship between burnout and turnover intention ($\beta = .49$, $p < .001$) confirms [17] chain mediation model in professional contexts. The most significant theoretical contribution is the confirmed sequential mediational pathway (indirect effect = .094, 95% CI [.071, .124]), which extends Chen and Zhou [9] research on AI stress by demonstrating how technological changes translate into workforce behaviors through psychological mechanisms. The protective roles of technology self-efficacy ($\beta = -.19$, $p < .001$) and organizational support ($\beta = -.24$, $p < .001$) strengthen [7] findings on psychological capital as a moderator between technostress and work-exhaustion. Practically, these findings suggest organizations should implement strategic approaches to generative AI adoption, including phased implementation with adequate training, confidence-building interventions, supportive technological adaptation contexts, and early stress management programs. As Brougham and Haar [12] demonstrated, technological disruption significantly influences job insecurity and turnover intentions, underscoring the importance of addressing these psychological processes. The differences observed across technological specializations echo [24] work on employees' challenge-hindrance appraisals toward STARA awareness, suggesting differentiated approaches for various professional groups. Although this study enhances knowledge pertaining to the sociotechnical aspects of fulfilling generative AI systems, further research should try to incorporate longitudinal approaches, broaden the demographic scope, include undisguised observational metrics [10] look into additional mediating mechanisms like perceived professional identity threats, and analyse specific applications of generative AI and their unique impacts on work-related psychology and sociology.

6. Conclusion

This research strongly validates the hypothesised model that technology stress perception and career burnout mediate the relationship between generative AI tools usage and turnover intention among young tech talents. The results underscore the idea that generative AI tools affect turnover intention primarily through a series of psychological processes rather than through straightforward impacts. The significant indirect pathway ($\beta = .094$, 95% CI [.071, .124]) demonstrates how technological change creates stress perceptions that contribute to burnout, which ultimately manifests as turnover intention. Protective factors identified include technology self-efficacy, which reduces technology stress ($\beta = -.19$, $p < .001$), and organizational support, which mitigates burnout ($\beta = -.24$, $p < .001$). These findings offer important theoretical contributions by extending Job Demands-Resources theory to emerging AI contexts, advancing technostress literature specifically for generative AI applications, and establishing empirical support for sequential psychological processes linking technological change to workforce behaviors. Practical implications include the need for strategic implementation approaches, confidence-building interventions, supportive organizational contexts, and early stress management programs. Organizations must balance technological advancement with employee wellbeing by investing in supportive implementation practices and targeted interventions that address psychological impacts at each stage of the chain mediation process. As generative AI continues transforming work across sectors, understanding these human dimensions becomes crucial for maintaining workforce stability while capturing technological benefits. Future research should explore

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these relationships longitudinally across diverse professional contexts and demographic groups to further enhance our understanding of how AI technologies shape workplace psychology and behavior.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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