

WHEN ARTIFICIAL INTELLIGENCE THREATENS CAREERS: A MODERATED MEDIATION MODEL OF JOB INSECURITY, EMOTIONAL EXHAUSTION, AND TURNOVER INTENTION

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Abstract

The rapid integration of artificial intelligence into organizational operations has intensified employee concerns about job continuity, yet the psychological pathway linking such concerns to workforce withdrawal remains incompletely specified. Drawing on Conservation of Resources theory, this study examines how AI-induced job insecurity influences turnover intention, tests emotional exhaustion as a mediating mechanism, and evaluates perceived organizational support as a boundary condition attenuating the insecurity-exhaustion relationship. Using a quantitative, explanatory design, cross-sectional survey data were collected from 312 manufacturing employees selected through purposive sampling, and the moderated-mediation model was analyzed via partial least squares structural equation modeling (PLS-SEM) in SmartPLS. The measurement model satisfied reliability, convergent, and discriminant validity criteria. Results indicate that AI-induced job insecurity significantly increases turnover intention both directly and indirectly through emotional exhaustion, which functions as a partial mediator, confirming that perceived technological threat operates as a resource-depleting stressor driving defensive withdrawal. Perceived organizational support significantly weakens the insecurity-exhaustion relationship, substantiating a resource-substitution mechanism and helping reconcile prior inconsistent findings on the buffering role of support. The study extends Conservation of Resources theory by integrating its loss and gain dynamics within a single mechanism in the AI workplace and by treating AI-induced insecurity as a distinct construct.

INTRODUCTION

Artificial Intelligence has evolved from a sideline novelty to an integral operational technology, transforming the way work is designed, allocated and done in virtually every industry of the global economy. The increasing use of generative and autonomous systems to speed up processes and cut costs is leading to a basic question: will there still

be a need for employees? Emotional exhaustion may be related to high AI awareness and perceived AI threats, as employees have concerns that their jobs might be replaced by AI, leading to a sense of job insecurity and stress (Teng et al., 2024). This apprehension is important because it is not dependent on the actual displacement, but rather on the perception of being vulnerable which

results in psychological stress. Technological change is an important organizational disruption that poses a threat to job security, and increases anxiety and role ambiguity (Yam et al., 2024). It is important, therefore, that scholars, managers and policymakers understand these human consequences if they want to ensure organizational performance and wellbeing of their workforce in the face of fast technological change.

In this general change, service and routine-based sectors are particularly vulnerable, as their jobs are easily replaced by automation. The hospitality industry is especially susceptible to automation and technological disruption due to its reliance on routine and manual tasks, history of limited career progression, repetitive roles, and high emotional labor, which are all tasks that can be performed by technology (Chuang, 2024). In these environments, when workers feel their role is dispensable, there are limited internal promotion opportunities and this exacerbates the sense of job insecurity due to AI. This renders labor-intensive service and manufacturing settings a key and instructive context to explore the relationship between perceptions of AI threat and psychological strain, and ultimately withdrawal from the organization.

AI induced job insecurity is the subjective perception of a threat to the continuity and stability of job by employees due to intelligent technologies (Shoss, 2017). Previous research has shown that this is an evaluation that is associated with a series of negative consequences. Empirical evidence indicates that AI awareness has a positive influence on job insecurity, which in turn contributes to emotional exhaustion, and that AI-induced job insecurity negatively impacts psychological safety and increases knowledge-hiding behaviors (Zheng & Zhang, 2025; Kim & Kim, 2024). Core dimension of burnout is emotional exhaustion, which is a state of depleted resources that is the precursor to disengagement. AI adoption has been found to make employees feel more insecure about their jobs, and thus more likely to leave their jobs, and awareness of AI is related to turnover intentions (Lingmont & Alexiou, 2020; Li et al., 2019).

There are three particular gaps in knowledge. Second, there is a contextual gap as most of the literature focuses on the cognitive and career outcomes, and little work has been conducted on how the stress induced by AI can overflow to other contexts (Teng et al., 2024), and thus, the affective mechanism between insecurity and organizational withdrawal has not been fully specified in a single integrated model. Second, an empirical incongruence is related to the buffering effect of organizational resources. The mixed evidence suggests that perceived organizational support may act as a protective resource for some individuals, but not for others. For example, perceived organizational support moderated the effects of stress on burnout for employees in the healthcare industry (Tham et al., 2023), but it was not a significant moderator between job insecurity and quitting intention among hotel employees (Appannan et al., 2022). This split indicates there is still room for debate as to the circumstances in which support reduces strain related to AI. Third, there is a theoretical lack in combining the exhaustion pathway and the support buffer into a single moderated-mediation model based on a resource logic, instead of considering them as two distinct effects. These gaps are not just theoretical; they are practical, as managers need to know if there is any point in the money they allocate to organizational support being a worthwhile investment to counter the retention costs of AI security.

The issue is real-world: as companies ramp up their use of AI, there's a danger they'll end up alienating customers, albeit indirectly, by operating on a psychological level that they don't monitor or control. If insecurity eats into the emotional bank account of employees, a technological upgrade becomes a liability and costs to replace workers, service disruption and loss of tacit knowledge ensue. This is a problem that needs to be solved as financial considerations are often the only ones taken into account when calculating the benefits of automation, and this can lead to decisions that are seemingly efficient but actually put the stability of the organization at risk. Therefore, this study aims to investigate the relationship between AI-

induced job insecurity and turnover intention, as well as to examine whether emotional exhaustion serves as a mediator between AI-induced job insecurity and turnover intention and to investigate whether perceived organizational support (POS) moderates the relationship between AI-induced job insecurity and emotional exhaustion. The study does so by identifying the affective pathway by which AI threat leads to turnover and a managerially actionable resource that may buffer the impact of AI threat.

The study is based on the Conservation of Resources theory (Hobfoll, 1989) which suggests that when employees are threatened with a loss of resources, they become defensive and act in conservation behaviors to protect against further loss of resources (Hobfoll et al., 2018), and that insecurity, exhaustion and support can be viewed as interacting resource dynamics. Theoretically the study builds on the Conservation of Resources theory by conceptualizing emotional exhaustion as the affective link between AI-induced insecurity and turnover intention. In practice, it helps to understand if the organizational support is a successful buffer or not and this is used to inform retention strategy when adopting AI. It puts these dynamics in the context of a workforce that is extremely vulnerable to automation, and provides direct evidence that is relevant to the industries most exposed to technological substitution.

Literature Review

Theoretical Foundation

This study is guided by Conservation of Resources theory. The theory is that people try to hold on to and preserve resources, and what is threatening is the loss of valued resources either in actuality or potentiality (Hobfoll, 1989). Resources include objects, personal attributes, situations (like employment security) and energies (time, knowledge). There are two principles which are central. First, the salience of resource loss is greater than that of resource gain, and an equivalent loss has a greater psychological impact than an equivalent gain (Hobfoll, 2001). Secondly, people have to invest resources to prevent a loss, to recover from a loss, and to get more resources, and

that is why threatened employees take defensive stances. What's important to note for the current model is that COR considers the risk of losing a job to be enough to trigger strain, so even if an employee is not displaced, if they feel they are at risk of losing their job due to AI, it can lead to strain. If continuity of employment is a valued condition resource, then employees start a trajectory of losing resources which leads to loss spirals (Hobfoll et al., 2018). Emotional exhaustion is the observable result of this depletion and withdrawal behaviors, including turnover intention, are the defensive conservation response whereby employees attempt to get out of a resource-draining situation.

Although COR is the most prevalent lens for workplace stress research, this lens has some important drawbacks when applied to AI settings. Much past research uses COR descriptively as a post hoc rationalization of observed correlations without developing testable mechanisms, and historically, there has been criticism for the lack of clarity of what constitutes a resource (Halbesleben et al., 2014). However, studies often hypothesize that the loss side of the model is insecurity depleting resources and fail to specify the resource-gain side of the model, that is, which resources buffer the depletion and under what circumstances (Hobfoll et al., 2018). The applications to AI-specific stressors exacerbate this: many recent studies include AI awareness and burnout (Kong et al., 2021; Teng et al., 2024) and end with documenting depletion, rather than the moderating logic of resource substitution is sufficiently supported empirically. Moreover, previous research typically uses single-source cross-sectional designs, which cannot account for the temporal loss spirals COR proposes, and thus makes causal inferences less robust. The present study seeks to fill these gaps by employing COR not only as a way of categorizing relationships, but as a means to specify a mediated pathway (insecurity, exhaustion, turnover) and a resource-buffering condition (perceived organizational support), thus addressing both the loss and gain aspects of the theory and expanding its explanatory scope into the AI workplace.

Relationship Among Variables

This idea is theoretically sound and rooted in COR's loss logic: When a valued condition resource is threatened, employees defensively attempt to exit to prevent further loss (Hobfoll, 1989). AI-induced job insecurity builds on the notion of classic job insecurity and adds the threat that it is specifically from intelligent technologies that can replace tasks. This connection has been empirically confirmed more and more. Adoption of AI has been found to lead to job insecurity among employees, which in turn is linked to a stronger preference to leave (Lingmont & Alexiou, 2020; Li et al., 2019), and awareness of AI is linked to turnover intentions. The findings from recent studies conducted in Turkey's SMEs suggest that AI uncertainty increases turnover intention, in part due to its impact on organizational commitment (Galanis et al., 2024). Similarly, Hospitality research indicates that AI-driven job insecurity prompts employees to reassess their career paths, resulting in not only intentions to quit their jobs but also leave the industry entirely (Chuang, 2024). The similarities in the manufacturing, service and SME contexts indicate a strong and pervasive effect.

However, the trend is not consistent and careful analysis shows that there are contingencies that make the positive correlation not straightforward. Some employees react to the threat of insecurity by proactively coping or entrenchment, depending upon the availability of substitute resources and the appraisal style (Frontiers, 2025). Evidence supporting the relationship between insecurity and turnover is often cross-sectional and comes from a single source, leading to concerns about common-method inflation of the insecurity-turnover association, and samples are often sampled from a single national context, primarily China, limiting cross-cultural generalizability. These inconsistencies indicate that the direct impact of these processes, although actual, can be mediated by other affective processes and is not independent of them. This thinking encourages looking into the mediating mechanism and the

first hypothesis and the following pathway are developed.

H1: AI-induced job insecurity is positively related to turnover intention.

This connection is rooted in the depletion premise of COR theory, which states that when the appraisal of employment threat is ongoing, the psychological energy that employees would normally conserve is used up, and emotional exhaustion is the affective byproduct of the energy drain (Hobfoll, 2001). Loss is more salient than gain and chronic insecurity maintain a vigilant and resource expending state of employees which reduces emotional resource. This logic is very similar to that of empirical work. Emotional exhaustion is linked to high AI awareness and perceived AI threat, where employees are concerned about the potential for job replacement by AI, leading to job insecurity and stress (Teng et al., 2024). The longitudinal evidence and mediation results suggest that AI awareness is positively associated with job insecurity, which in turn is associated with emotional exhaustion (Zheng & Zhang, 2025), and related findings show that AI-induced job insecurity decreases psychological safety and increases knowledge-hiding (Kim & Kim, 2024). This uniformity in designs increases trust in a depletion mechanism for AI related threat.

However, there are interpretive tensions in the evidence base that need to be critically considered. Some studies use the terms AI awareness and job insecurity interchangeably, making it unclear whether the sense of salience of AI or the sense of job insecurity is causing exhaustion (Kong et al., 2021). This is a true empirical inconsistency: When insecurity is measured separately, effects on exhaustion are consistent and strong, but when it is incorporated into a wider AI-awareness scale, effects are less consistent and mechanisms are less clear. Additionally, contextual differences also play a role, as the effects of these factors seem to be more pronounced in high-emotional-labor industries like hospitality, where the resource demands are already high (Chuang, 2024). This moderating context signal is important because it suggests that depletion is not permanent, but

rather dependent upon the resource context, as explored in H4. Once insecurity has been established as a drain on emotional resources, the model next stipulates that this is passed on to withdrawal.

H2: AI-induced job insecurity is positively related to emotional exhaustion.

The mediating role of exhaustion is a logical consequence of the loss-spiral corollary of COR, which states that a resource threat (insecurity) can lead to a depletion (exhaustion) and then to a defensive withdrawal response (turnover intention) as employees try to leave the draining context before further loss can occur (Hobfoll et al., 2018). This places exhaustion as the affective pathway transforming a threat appraisal from the cognitive to the behavioral level. Evidence is growing: studies show that negative cognition related to AI is associated with emotional exhaustion, which in turn is a direct predictor of reduced commitment and turnover processes (Teng et al., 2023); and emotional exhaustion has been found to be a proximal antecedent of turnover in all occupational settings (Wright & Cropanzano, 1998). The structural plausibility of the indirect pathway to withdrawal (AI awareness to insecurity to exhaustion) is supported by studies modeling serial pathways between AI awareness and insecurity to exhaustion (Zheng & Zhang, 2025).

However, crucially, the mediation is likely to be incomplete and there are mixed views on the extent of mediation in the literature. Results showing a direct link between insecurity and turnover (Li et al., 2019) suggest that exhaustion only partially transmits the relationship between insecurity and turnover. This ambiguity is exacerbated by methodological limitations: many mediation tests use cross-sectional data, and these data do not allow for the temporal ordering that mediation logically demands, and bootstrapped indirect effects estimated on single-wave data may overestimate the mediation mechanism. Pathway is also moderated by contextual factors: in the absence of alternative employment, intention to quit may not lead to actual quitting, because of the

following: Exhausted employees may not quit, even if they intend to do so. The inconsistencies suggest that the indirect effect is genuine but limited, and that the magnitude of the indirect effect is dependent on the resources available to compensate for depletion. This dependence is directly motivating the following moderating hypothesis.

H3: Emotional exhaustion mediates the relationship between AI-induced job insecurity and turnover intention.

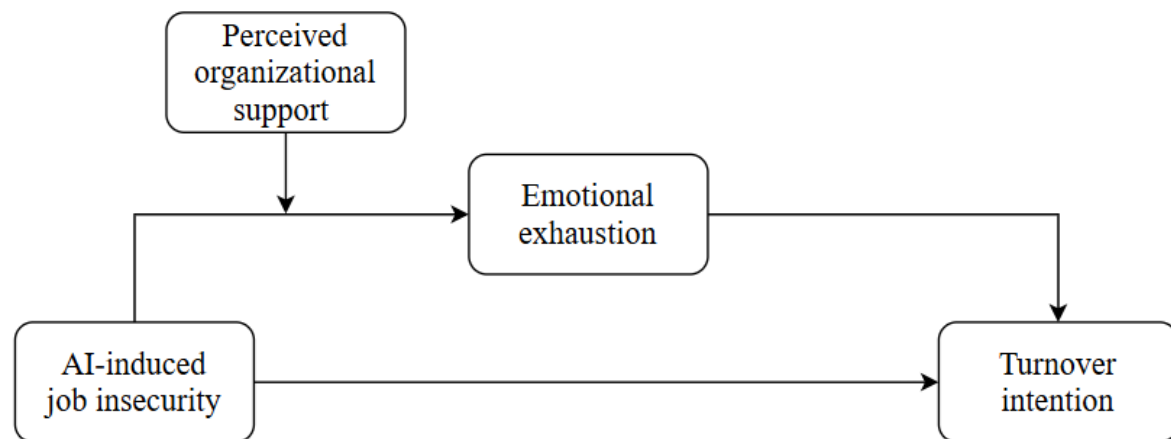
Insecurity is a condition resource that can be depleted by the lack of it, and COR is a resource that can make up for the depleting condition, slowing the rate of exhaustion (Hobfoll, 1989). If employees perceive that the organization cares for and will support them, then the fear of losing to AI is somewhat offset by a fearless gain of resources which helps to reduce the loss spiral. Evidence suggests that perceived organizational support (POS) buffers the impact of stress on burnout (Tham et al., 2023), and AI-related studies reveal that POS is a moderating variable for the relationship between AI-induced stress and employees' engagement and psychological capital in the hotel industry (Hou & Fan, 2024). The moderated mediation effect of perceived robot threat on turnover intention through positive emotions (IJSSRR, 2025) was confirmed in a parallel study of manufacturing employees, which further supports the substitution logic.

However, this buffering effect is not empirically supported, and constitutes a true contradiction which the present study has to deal with. However, some studies show that perceived supervisor support does not significantly moderate the relationship between job insecurity and intention to quit among hotel employees (Appannan et al., 2022), indicating that organizational resources might not buffer the effects of job insecurity when it is perceived as structural and irreversible, as is often the case with AI displacement. This difference makes sense in terms of moderator specificity (organizational versus supervisor support), the time of measurement, and the nature of the context (moderate versus existential threat

to the job). In methodologic terms, other limitations of comparability are also due to underpowered interaction tests and single-context samples. Combining these tensions, the resource-substitution mechanism is theoretically interesting, conditionally supported, and has not been examined in connection with AI-specific

insecurity in an integrated moderated-mediation model. The present study is aimed at resolving this ambiguity and represents the main empirical contribution.

H4: Perceived organizational support moderates the relationship between AI-induced job insecurity and emotional exhaustion.



Methods

The research philosophy used in this study is positivist, as the research aims involve objectively measuring pre-defined constructs and testing relationships that have been derived from theory (Saunders et al., 2019). Conservation of Resources theory is a theory with specific, testable predictions about how AI-related job insecurity consumes resources and leads to withdrawal, thus a positivist approach is epistemologically congruent with the confirmatory purpose of the study. Accordingly, it is a deductive study, which progresses from theory to hypotheses to observation; the four hypotheses are formulated a priori from COR and tested against the numerical data, thus enabling the model to be corroborated or refuted, but not inductively developed (Bryman & Bell, 2015).

Hence, the study adopts a quantitative and explanatory research design appropriate for the study of causal and conditional relationships among latent variables and for testing a conditional mediation model that could not be statistically analyzed by qualitative research. This design is operationalized using a cross-sectional

survey strategy which allows for efficient and standardized data collection from a large sample and facilitates the correlational and path analyses required by the hypotheses. The cross-sectional horizon is justified on practical grounds and because the model posits contemporaneous psychological appraisals, but it is recognized that this horizon limits strong causal inference compared to longitudinal alternatives (Podsakoff et al., 2003). The target group includes manufacturing workers whose jobs are vulnerable to automation, where the sense of insecurity over AI is most relevant. A non-probability technique of purposive sampling is used, and the sample size is determined based on the SEM guidance which is at least 200-300 respondents to achieve adequate statistical power; although it is not strictly generalizable, it is more relevant because the respondents are those to whom the constructs are meaningful.

Data is gathered using a structured questionnaire that is self-administered and given to eligible employees, after informed consent, assurances of anonymity, confidentiality, and voluntary

withdrawal rights, in line with research ethics. Content and construct validity are supported by the rewording of items to fit the context, expert review, and pilot testing to establish clarity and preliminary reliability for all constructs, which are measured reflectively using multi-item scales adapted from previously validated studies. Partial least squares structural equation modeling (PLS-SEM) is employed to analyze the data in SmartPLS software, which is suitable for complex models with mediation and moderation analysis, and is tolerant of non-normal data and has a predictive orientation; the measurement model is tested for reliability and validity before testing the structural-path and interaction (Hair et al., 2022).

Data Analysis

Data Screening and Cleaning

The data set was screened for quality prior to analysis. There were minimal missing values (<5%) and these were replaced using mean substitution, which is acceptable at this level (Hair et al., 2022). Univariate outliers were examined using standardized z scores (± 3.29) and multivariate outliers were examined using Mahalanobis distance, and no cases were found to be problematic. Skewness and kurtosis were used to assess normality, which was set at ± 2 . Multicollinearity was checked and found acceptable ($VIF < 3.3$), and common method bias was assessed using Harman's single factor test, which accounted for less than 50% of the variance (Podsakoff et al., 2003).

Table 1. Demographic Profile of Respondents

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	189	60.6
	Female	123	39.4
Age	21–30	108	34.6
	31–40	121	38.8
	41–50	61	19.6
	Above 50	22	7.0
Education	Diploma/Below	74	23.7
	Bachelor's	158	50.6
	Master's/Above	80	25.7
Experience	Less than 3 years	89	28.5
	3–7 years	134	42.9
	8–12 years	61	19.6
	More than 12 years	28	9.0
Sector	Manufacturing	312	100.0
Position	Operational staff	171	54.8
	Supervisory	97	31.1
	Managerial	44	14.1

A total of 312 manufacturing employees participated, with a majority of male participants (60.6%), which aligns with the known gender distribution of workers in the manufacturing sector (Chuang, 2024). The age distribution of respondents was heavily skewed towards the early-to-mid career segment (21 to 40 years old), where AI-related displacement issues are particularly

relevant. The majority of respondents had a bachelor's degree (50.6%) and had 3 to 7 years of organizational experience (42.9%) which indicated that they had enough experience to have developed stable assessments of employment security and support. The high percentage of operational staff (54.8%) occupations most vulnerable to automation increases the theoretical

significance of the sample because these occupations face the resource threats central to the

Conservation of Resources framing of the study (Hobfoll, 1989) that are posed by AI.

Table 2. Reliability and Item-Total Statistics

Construct	Item	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted	Construct Cronbach's Alpha
AI-Induced Job Insecurity (AIJI)	AIJI1	0.68	0.83	0.86
	AIJI2	0.72	0.82	
	AIJI3	0.70	0.82	
	AIJI4	0.71	0.82	
Emotional Exhaustion (EE)	EE1	0.74	0.85	0.88
	EE2	0.76	0.84	
	EE3	0.73	0.85	
	EE4	0.71	0.86	
Perceived Organizational Support (POS)	POS1	0.70	0.84	0.87
	POS2	0.73	0.83	
	POS3	0.75	0.83	
	POS4	0.69	0.85	
Turnover Intention (TI)	TI1	0.77	0.82	0.85
	TI2	0.72	0.84	
	TI3	0.70	0.84	

All constructs showed satisfactory internal consistency, with the alpha ranging from 0.85 to 0.88, which were all above 0.70 and below 0.90, signifying reliable but not redundant items (Hair et al., 2022). All item-total corrected correlations were above 0.30, which indicated that each item was an important part of its construct. Most importantly, none of the items' "alpha if deleted" scores were higher than the alpha for the construct, so that deletion would not increase the

reliability, and all items were kept. The fact that the values were consistent across theoretically different constructs, from a stressor (AIJI) to a strain (EE), to a resource (POS), to an outcome (TI), indicates that the measurement instrument was able to measure the latent constructs with stable precision, thus providing a foundation for subsequent structural testing (Nunnally & Bernstein, 1994).

Table 3. Pearson Correlation Matrix

Variable	Mean	SD	1	2	3	4
AIJI	3.62	0.78	1			
EE	3.48	0.82	0.54**	1		
POS	3.21	0.85	-0.38**	-0.42**	1	
TI	3.55	0.80	0.51**	0.58**	-0.44**	1

Note. ** $p < 0.01$ (two-tailed).

Preliminary support for the hypothesized relationships was obtained with the correlation matrix. In line with the Conservation of Resources

theory that resource threat leads to strain and withdrawal (Hobfoll et al., 2018), AI-induced job insecurity was positively and significantly

associated with emotional exhaustion ($r = 0.54$, $p < 0.01$) and turnover intention ($r = 0.51$, $p < 0.01$). Emotional exhaustion was most strongly correlated with turnover intention ($r = 0.58$, $p < 0.01$), indicating that it would likely be a mediator. As predicted, perceived organizational support negatively correlated with all stress-related

variables, with the highest correlation being with exhaustion ($r = -0.42$, $p < 0.01$). All correlations were less than 0.85, which initially indicated that there was no multicollinearity and that the measurements were distinctively different prior to the measurement-model assessment.

Table 4. Measurement Model, Reliability and Convergent Validity

Construct	Item	Outer Loading	Cronbach's Alpha	rho_A	CR	AVE
AIJI	AIJI1	0.78	0.86	0.87	0.90	0.69
	AIJI2	0.84				
	AIJI3	0.85				
	AIJI4	0.85				
EE	EE1	0.82	0.88	0.89	0.92	0.73
	EE2	0.87				
	EE3	0.86				
	EE4	0.87				
POS	POS1	0.80	0.87	0.88	0.91	0.71
	POS2	0.86				
	POS3	0.87				
	POS4	0.84				
TI	TI1	0.88	0.85	0.86	0.91	0.77
	TI2	0.87				
	TI3	0.88				

Reliability and convergent validity of the measurement model was good for all reflective constructs. All outer loadings were above the 0.70 criterion (0.78-0.88), which indicated reliability of the indicators (Hair et al., 2022). The internal consistency was always good: Cronbach's Alpha (0.85-0.88), rho_A (0.86-0.89) and Composite Reliability (0.90-0.92) were all above 0.70, while Cronbach's Alpha was below 0.90, demonstrating reliability without redundancy. Convergent

validity was established by the fact that all of the AVEs were greater than 0.50 (ranging from 0.69 to 0.77), which indicated that the constructs accounted for more than half of the variance in the indicators. The combination of these criteria shows that the constructs were measured to a sufficient degree to allow for confident interpretation of the structural paths, thus meeting the requirements for valid latent-variable analysis (Henseler et al., 2015).

Table 5. Discriminant Validity

	AIJI	EE	POS	TI
AIJI	0.83			
EE	0.54	0.85		
POS	-0.38	-0.42	0.84	
TI	0.51	0.58	-0.44	0.88

Discriminant validity was established through two complementary criteria. Under the Fornell-Larcker criterion, the square root of each

construct's AVE (diagonal, 0.83–0.88) exceeded its correlations with all other constructs, confirming

that each construct shared more variance with its own indicators than with competing constructs.

Table 6. Structural Model, Path Coefficients and Hypothesis Testing

Hypothesis	Path	β	t value	p value	95% CI (LL, UL)	Decision
H1	AIJI $\rightarrow$ TI	0.24	4.31	0.000	[0.13, 0.35]	Supported
H2	AIJI $\rightarrow$ EE	0.49	9.87	0.000	[0.39, 0.58]	Supported
H3	AIJI $\rightarrow$ EE $\rightarrow$ TI	0.21	6.02	0.000	[0.14, 0.28]	Supported
H4	POS $\times$ AIJI $\rightarrow$ EE	-0.17	3.44	0.001	[-0.27, -0.07]	Supported

The structural model supported all four hypotheses. AI-induced job insecurity exerted a significant direct effect on turnover intention ($\beta = 0.24$, $t = 4.31$, $p < 0.001$), supporting H1 and confirming that perceived AI threat prompts defensive withdrawal, consistent with COR's loss logic (Hobfoll, 1989; Lingmont & Alexiou, 2020). The strongest path linked insecurity to emotional exhaustion ($\beta = 0.49$, $t = 9.87$, $p < 0.001$), corroborating H2 and echoing evidence that AI threat depletes affective resources (Teng et al., 2024). The indirect effect through exhaustion was significant with a bootstrapped CI excluding zero ($\beta = 0.21$, $t = 6.02$), supporting H3; as the direct effect remained significant, exhaustion operates as a *partial* mediator, indicating that withdrawal is transmitted both directly and through resource depletion (Zheng & Zhang, 2025). Finally, the negative interaction term ($\beta = -0.17$, $t = 3.44$, $p = 0.001$) supported H4, demonstrating that perceived organizational support significantly attenuates the insecurity-exhaustion relationship. This buffering effect substantiates the resource-substitution mechanism and helps reconcile prior inconsistent findings on POS moderation (Tham et al., 2023; Appannan et al., 2022), suggesting support functions effectively even against technologically driven threat. The model explained meaningful variance in both exhaustion ($R^2 = 0.41$) and turnover intention ($R^2 = 0.46$).

Discussion

The emergence of the AI-induced job insecurity as a significant predictor of turnover intention aligns with the defensive aspect of the Conservation of Resources theory: When employees perceive their work as a valued condition resource threatened by

AI, withdrawal is a way to avoid additional loss (Hobfoll, 1989). This is because the perception of displacement - and not just displacement itself - is enough to trigger a conservation action, and that is why insecurity converts to leaving intentions even when jobs are still seemingly secure. This finding aligns with evidence of an increased risk of leaving preferences when using AI (Lingmont & Alexiou, 2020; Li et al., 2019) and hospitality findings of reassessing career paths when feeling insecure with AI (Chuang, 2024). The impact was seen in manufacturing, where mobility is limited, too: exposed workers said they planned to leave, indicating that the prospect of leaving outweighed the "glue" of low mobility.

The high correlation between insecurity and emotional exhaustion and the partial mediation of emotional exhaustion by turnover sheds light on the threat becoming behavior. The affective energies of sustained vigilance towards an uncontrollable stressor deplete, and exhaustion acts as the strain that transforms the cognitive appraisal into withdrawal, in line with the loss-spiral corollary, which suggests that initial threat can lead to exhaustion and defensive exit (Hobfoll et al., 2018; Zheng & Zhang, 2025). This synthesis is consistent with the findings that link AI threat with exhaustion and decreased commitment (Teng et al., 2024). However, the partial rather than full mediation is analytically significant: it suggests that insecurity leads to turnover not only because of exhaustion, but also because of the plausibly cognitive commitment erosion, which helps to resolve the apparent tension between studies that focus on direct effects (Li et al., 2019) and studies that focus on affective mechanisms (Teng et al., 2023).

The buffering effect of perceived organizational support on the insecurity-exhaustion relationship addresses a direct conflict in the literature. Support served as a substitute resource to buffer depletion, slowing the loss spiral before it becomes more severe (Hobfoll, 2001). This supports evidence that POS helps to buffer stress-burnout relationships (Tham et al., 2023) and contradicts evidence supporting failed to buffer insecurity effects (Appannan et al., 2022). Moderator specificity and threat framing offer a plausible explanation for the divergence: organizational support may be enough against AI-related strain, but not necessarily when it comes to supervisor-level support, and buffering may be even less effective when the displacement is perceived as being completely irreversible. That support buffered here indicates that AI threat was seen as somewhat manageable and not existential.

Theoretical Implications

The findings suggest an extension of the Conservation of Resources theory to the AI workplace, as the loss and gain aspects of the theory are shown to work simultaneously in a single mechanism. While many previous applications of COR have used the construct descriptively to label depletion (Kong et al., 2021; Teng et al., 2024), the current study provides a testable moderated mediation model where threat depletes (insecurity → exhaustion), exhaustion turns over (exhaustion → turnover), and a countervailing resource substitute (POS buffering) engages the resource-investment principle that was underspecified in earlier work (Hobfoll et al., 2018). Positioning the insecurity brought about by AI as a separate condition-resource threat, as opposed to incorporating it into a general AI-awareness construct, allows for a more precise measurement and helps to resolve the construct overlap that has complicated previous estimates of effects. The results also confirmed buffering for a technologically driven stressor, going beyond the skeptical findings of previous research, which assumed that structural threats are invulnerable to organizational resources.

Practical Implications

The findings for managers are that the human side of AI implementation is not inevitable and uncontrollable. Interventions that address the mechanism directly—such as reducing affective depletion, communicating transparently about how AI will transform roles instead of replace them, and implementing AI in a participatory manner—can help reduce turnover. The buffering effect of perceived organizational support provides organizations with a lever to act: investing in support signals can help reduce the cost of retaining staff even in the face of high automation efforts, and should therefore be included in the financial argument for AI. The high exposure of effects on operational staff highlights the importance of sector-level reskilling frameworks, which target the most at risk from substitution for policymakers.

Limitations and Future Research

The cross-sectional design limits causal interpretations and longitudinal or multi-wave studies would be better suited to capture the loss spirals theorized by COR. The sample is purposive, single-sector and single country, which restricts the generalizability, replication is warranted across other industries and cultures. Even with methodological efforts to prevent common method problems, they are still a possibility if self-report is the sole method used. Future research might include the testing of other mediators (e.g., commitment erosion), thresholds that might be curvilinear or an "existential threat" at which POS buffering is ineffective, and a comparison of the types of support to account for the inconsistencies in moderation effects reported in the literature.

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