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From Ai-Induced Job Insecurity to Burnout: A Job-Demands Resource Model of Job Stress, Meaningfulness of Work, And Self-Efficacy in Ai Learning Among Front-Line Employees in Indonesia

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Abstract

The rapid adoption of artificial intelligence (AI) is reshaping organizational structures and employment landscapes, raising concerns about job insecurity and employee well-being. This study examines the effect of AI-induced job insecurity on burnout among frontline employees in Indonesia, drawing on the Job Demands–Resources (JD-R) framework. Specifically, it investigates job stress and meaningfulness of work as mediating mechanisms and self-efficacy in AI learning as a moderating resource. A cross-sectional survey was conducted with 325 frontline employees across sectors where AI adoption is increasing, and data were analyzed using Structural Equation Modeling in Jamovi. The results indicate that AI-induced job insecurity significantly increases employee burnout, both directly and indirectly. Job stress was confirmed as a positive mediator, while meaningfulness of work functioned as a negative mediator, highlighting the dual role of demands and resources in shaping burnout. Furthermore, self-efficacy in AI learning moderated the insecurity–burnout relationship, such that employees with higher efficacy were less adversely affected. These findings extend the JD-R model by integrating AI-related job insecurity and demonstrating the dual processes of stress elevation and resource erosion. The study offers practical implications for organizations to prioritize transparent communication, reskilling initiatives, and meaning-enhancing practices to safeguard employee resilience in the era of digital transformation.

Keywords: *AI-induced job insecurity; Job Demands–Resources model; Job stress; Burnout; Frontline employees.*

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INTRODUCTION

The accelerating adoption of Artificial Intelligence (AI) and automation is transforming the global labor market by reshaping organizational structures, altering skill requirements, and challenging traditional forms of employment security. AI systems increasingly replace both cognitive and routine manual tasks, positioning themselves as a disruptive force in the Fourth Industrial Revolution (George et al., 2025; Tien, 2020). Frey & Osborne (2017) estimated that nearly 47 percent of occupations in the United States are at high risk of computerization, particularly in logistics, administrative, and sales roles. Comparable projections for Indonesia suggest that approximately 23 million jobs could be displaced by automation by

2030, especially in manufacturing, healthcare, retail, and construction (Baadshah, 2025). These figures illustrate the profound structural changes driven by AI adoption and underline the urgency of examining their implications for employees' well-being.

Indonesia demonstrates particularly high sensitivity to these disruptions. A recent Fournier-Tombs et al. (2023) revealed that 85 percent of Indonesian workers are concerned about job insecurity linked to AI integration, a proportion significantly higher than the global average of 65 percent. This anxiety is compounded by unequal access to upskilling: while 44 percent of organizational leaders have engaged in AI-related training, only 14 percent of frontline employees (FLE) have done so. Such disparities highlight the precarious position of FLE, who are simultaneously most exposed to automation and least prepared to adapt.

Frontline employees form a strategically vital occupational group, characterized by direct customer interaction, routine task execution, and representation of organizational identity (Chatterjee et al., 2022; Singh, 2000). Yet they often occupy structurally disadvantaged positions marked by lower wages, restricted autonomy, and limited career advancement opportunities (Vivek & Ahmed, 2023). These vulnerabilities amplify their susceptibility to perceived job insecurity in the face of rapid technological substitution. For instance, Indomaret's integration of automated cashier systems and inventory technologies Alwi (2025) and PT Pos Indonesia's adoption of AI-powered robotics for parcel sorting Baltasar & Marbun (2025) exemplify concrete cases where human labor is displaced by technological capital.

This phenomenon has given rise to what scholar's term AI-induced job insecurity, defined as the subjective perception of potential job loss or deterioration in employment security caused by the diffusion of AI into organizational processes (Kim, 2024; Sverke et al., 2002). Unlike actual unemployment, job insecurity reflects a psychological state associated with anxiety, stress, and diminished well-being (Fan & Qian, 2023; Üngüren et al., 2021). Prolonged exposure to such insecurity is a well-documented antecedent of burnout, characterized by emotional exhaustion, depersonalization, and reduced personal accomplishment (Maslach et al., 2001).

Despite the growing body of research on AI and labor disruption, the psychological mechanisms through which AI-induced job insecurity affects employees remain underexplored, particularly in developing economies such as Indonesia. Much of the existing scholarship has emphasized macroeconomic impacts, such as productivity and employment shifts Goodwin et al. (2022); Yavorsky et al. (2022), while largely neglecting micro-level employee experiences. This omission represents a critical research gap, given that job insecurity may operate through elevated stress, diminished meaningfulness of work, and ultimately burnout, with serious implications for both individual well-being and organizational performance (Peng & Potipiroon, 2022; Soren & Ryff, 2023).

To address this gap, the present study adopts the Job Demands–Resources (JD-R) model Bakker & Demerouti (2017) as a guiding framework. AI-induced job insecurity is conceptualized as a novel job demand that initiates the health-impairment process leading to stress and burnout. Job stress is examined as a mediator of this process, while meaningfulness of work is treated as a job resource with the potential to buffer negative effects. Furthermore, self-efficacy in AI learning is incorporated as a personal resource, hypothesized to moderate the relationship by enabling employees to reinterpret technological disruption as a challenge rather than

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a threat (Kim, 2024).

By integrating these perspectives, this study extends the JD-R framework into the domain of technological disruption and provides empirical evidence on the psychological consequences of AI adoption for frontline employees in Indonesia. The findings are expected to enrich scholarly understanding of the intersection between AI and employee well-being, while offering practical insights for organizations in Southeast Asia seeking to preserve workforce resilience amid rapid digital transformation.

LITERATURE REVIEW

Theoretical Foundation

The Job Demands–Resources (JD-R) model offers a comprehensive framework for understanding how workplace characteristics shape employee well-being and performance (Bakker & Demerouti, 2017). According to this model, every occupation contains specific job demands and job resources. Job demands are aspects of the work that require sustained effort and are associated with physiological or psychological costs, such as workload, role conflict, or job insecurity. In contrast, job resources are aspects of the work that help achieve goals, reduce demands, or stimulate personal growth, such as autonomy, social support, or meaningfulness of work. The JD-R model proposes two parallel processes: a health-impairment process, where excessive demands lead to stress and burnout, and a motivational process, where sufficient resources foster engagement and well-being (Bakker & Demerouti, 2017).

In the present study, AI-induced job insecurity is conceptualized as a novel form of job demand. As frontline employees anticipate possible job loss or role transformation due to automation, they experience heightened cognitive and emotional strain that may lead to stress and ultimately burnout. Conversely, meaningfulness of work is treated as a job resource that can sustain intrinsic motivation and buffer the detrimental effects of insecurity. By integrating these constructs, the JD-R model provides a robust foundation for analyzing how technological disruption shapes employee well-being in Indonesia.

The JD-R framework is complemented by the Conservation of Resources (COR) theory, which posits that individuals strive to acquire, retain, and protect valued resources such as employment, status, or self-esteem (Hobfoll et al., 2018). Resource loss is considered disproportionately more powerful than resource gain, and prolonged resource depletion can trigger stress and burnout. AI-induced job insecurity threatens essential resources, including stable income and professional identity, which in turn provokes stress responses. From a COR perspective, frontline employees may attempt to compensate for threatened resources by overinvesting in work, which paradoxically increases the risk of exhaustion. This theoretical lens helps explain why job insecurity not only heightens stress but also interacts with perceptions of meaningfulness in complex ways.

Meaningfulness of work, defined as the perception that one's job is significant and purposeful, is a central motivational resource in the JD-R framework (Steger et al., 2012). High levels of meaningfulness have been shown to buffer the negative effects of job demands and enhance resilience (Allan et al., 2019). However, recent scholarship also highlights the ambivalent role of meaningful work: under conditions of chronic stress and limited organizational support, heightened meaningfulness may contribute to overcommitment and eventual burnout (Kim & Lee, 2024). This duality is particularly relevant for frontline employees in Indonesia, who may reframe their roles as meaningful when threatened by AI, yet simultaneously lack the resources to sustain prolonged effort without exhaustion.

Finally, the study incorporates self-efficacy in AI learning as a personal resource grounded in Social Cognitive Theory (Bandura, 1977). Self-efficacy refers to individuals' beliefs in their ability to execute actions necessary to manage prospective situations. In the context of AI adoption, employees with high AI-learning self-efficacy are more likely to view technological disruption as an opportunity to develop new skills rather than as a threat, thereby reducing the psychological impact of insecurity (Kim, 2024). However, research also indicates that individual resources may be insufficient when organizational and structural constraints are overwhelming (Rosso, 2014). The present study therefore tests whether self-efficacy moderates the relationship between AI-induced job insecurity and burnout, while acknowledging potential boundary conditions.

Together, the JD-R model, COR theory, and Social Cognitive Theory provide an integrated foundation for this research. AI-induced job insecurity is conceptualized as a demand that triggers the health-impairment process, job stress and meaningfulness of work are positioned as mediating mechanisms, and self-efficacy in AI learning is framed as a personal resource that may moderate outcomes. This theoretical integration allows the study to address the research gap by examining not only the direct impact of AI-induced job insecurity but also the psychological processes that explain or buffer its effects among frontline employees in Indonesia.

AI-Induced Job Insecurity, Job Stress, and Meaningfulness of Work

Job insecurity has long been recognized as a critical occupational stressor that undermines employee well-being and organizational performance. Traditionally, it refers to the perceived threat of job loss or deterioration in employment conditions (Greenhalgh & Rosenblatt, 1984). In the era of technological transformation, this construct has evolved into AI-induced job insecurity, defined as employees' fears that artificial intelligence and automation will displace human labor or substantially alter job roles (Kim, 2024; Sverke et al., 2002). Unlike cyclical unemployment linked to economic downturns, AI-induced insecurity represents a structural and enduring challenge, rooted in the diffusion of advanced technologies across industries.

Within the Job Demands–Resources (JD-R) model, job insecurity operates as a job demand that initiates the health-impairment process (Bakker & Demerouti, 2017). The anticipation of technological substitution consumes emotional and cognitive resources, increases vigilance, and elevates psychological strain, all of which are precursors of burnout. Burnout itself is characterized by emotional exhaustion, depersonalization, and diminished personal accomplishment (Maslach et al., 2001). Prolonged exposure to insecurity reduces individuals' ability to cope with daily demands, thereby accelerating progression toward burnout. Empirical evidence supports this pathway: job insecurity has been shown to predict higher levels of exhaustion and strain De witte et al. (2016), depressive symptoms, and burnout (Huo et al., 2021). In the context of technological disruption, AI-related threats further amplify stress and emotional exhaustion (Soren & Ryff, 2023). Based on these insights, the following hypothesis is proposed:

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H1: AI-induced job insecurity has a positive and significant effect on employee burnout.

Beyond its direct effect on burnout, AI-induced job insecurity also manifests in elevated stress. Job stress arises when job demands exceed employees' coping resources, leading to anxiety, strain, and physiological tension (Lazarus, 1966). Because insecurity is tied to uncertainty and perceived lack of control, it is widely recognized as a potent antecedent of stress (Sverke et al., 2002). In AI contexts, insecurity reflects structural transformations that directly threaten the continuity of work. Employees anticipating redundancy face persistent cognitive load and anticipatory worry, which heighten stress responses. Evidence shows that job insecurity significantly predicts stress levels and psychosomatic complaints Jiang & Lavaysse (2018) and contributes to absenteeism and reduced performance (Peng & Potipiroon, 2022). For frontline employees, who often have limited autonomy and insufficient opportunities for reskilling, the impact of insecurity on stress is particularly acute (Bansal et al., 2025). Accordingly, the following hypothesis is proposed:

H2: AI-induced job insecurity has a positive and significant effect on job stress.

At the same time, AI-induced job insecurity may erode a critical psychological resource: the meaningfulness of work. Meaningfulness is defined as the perception that one's work is significant and purposeful (Steger et al., 2012). As a job resource in the JD-R model, it fosters motivation, enhances resilience, and protects against the negative effects of demands (Allan et al., 2019). However, when employees perceive that their contributions can be replaced by machines, their sense of work significance is undermined. This symbolic devaluation diminishes intrinsic motivation, reduces coping capacity, and heightens vulnerability to stress and burnout. Prior research shows that job insecurity undermines perceived work significance and predicts exhaustion Hu et al. (2011), while diminished meaningfulness links insecurity to burnout (Soren & Ryff, 2023). For frontline employees in particular, whose roles are often routine and low in autonomy, the erosion of meaning under technological substitution is especially harmful (Van Doorn et al., 2023). Thus, this study proposes the following hypothesis:

H3: AI-induced job insecurity has a negative and significant effect on meaningfulness of work.

Job Stress and Employee Burnout

Job stress is a psychological state that emerges when job demands exceed an individual's capacity to cope, producing emotional strain, anxiety, and physiological tension (Lazarus, 1966). Within the Job Demands–Resources (JD-R) model, stress is a proximal outcome of excessive demands that initiates the health-impairment process (Bakker & Demerouti, 2017). Persistent exposure to stress depletes employees' emotional and cognitive resources, progressively increasing the likelihood of burnout.

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Burnout itself is characterized by three dimensions: emotional exhaustion, depersonalization, and diminished personal accomplishment (Maslach et al., 2001). Stress functions as the immediate driver of these symptoms by draining energy reserves, heightening negative affect, and impairing coping mechanisms. When employees experience sustained job stress, they often report feelings of fatigue, reduced enthusiasm, and a sense of detachment from their work, all of which accelerate the development of burnout.

Empirical evidence strongly supports this pathway. Sverke et al. (2002) found that stress consistently mediates the relationship between job insecurity and emotional exhaustion. Peng & Potipiroon (2022) similarly demonstrated that stress significantly predicted burnout among employees in high-demand service roles, underscoring its role as a central mechanism in the health-impairment process. More broadly, longitudinal studies confirm that chronic stress is among the strongest predictors of both psychological strain and occupational burnout across industries (De witte et al., 2016).

For frontline employees in Indonesia, who often face repetitive tasks, low autonomy, and limited support structures, the stress induced by AI-related job insecurity is likely to be particularly acute. Without adequate resources to buffer these demands, stress directly translates into exhaustion and burnout. Based on these theoretical and empirical insights, the following hypothesis is proposed:

H4: Job stress has a positive and significant effect on employee burnout.

Meaningfulness of Work and Employee Burnout

Meaningfulness of work is defined as the extent to which employees perceive their work as significant, purposeful, and aligned with personal values (Steger et al., 2012). Within the Job Demands–Resources (JD-R) model, it is considered a key job resource that fosters intrinsic motivation, resilience, and sustained engagement (Allan et al., 2019). Employees who derive meaning from their work are more capable of coping with stressors, as meaningfulness provides psychological energy and reinforces a sense of identity and purpose.

Theoretical and empirical evidence suggests that meaningfulness of work functions as a protective factor against burnout. When employees believe their tasks contribute to a larger purpose, they are less likely to experience emotional exhaustion and disengagement. Allan et al. (2019) found that meaningful work is negatively associated with burnout, while Hu et al. (2011) demonstrated that diminished work significance predicted higher exhaustion in organizational downsizing contexts. More recent findings confirm that meaningfulness serves as a buffer, allowing employees to reframe adverse experiences and maintain psychological well-being (Soren & Ryff, 2023).

For frontline employees, meaningfulness of work can be especially critical, given their limited autonomy and vulnerability to technological substitution. Even in routine or procedural roles, perceiving their contributions as valuable may help sustain motivation and reduce susceptibility to exhaustion. Conversely, when meaningfulness declines, employees lose one of the few available resources that protect against burnout, leaving them more exposed to the health-impairment process outlined in the JD-R model.

Based on this reasoning, the following hypothesis is proposed:

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H5: Meaningfulness of work has a negative and significant effect on employee burnout.

Job Stress as a Mediator

The Job Demands–Resources (JD-R) model suggests that job demands such as insecurity deplete employees' emotional and cognitive resources, triggering stress, which in turn accelerates the health-impairment process (Bakker & Demerouti, 2017). Stress thus functions not only as a direct outcome of insecurity but also as a proximal mechanism that links insecurity to burnout.

In the context of AI-induced job insecurity, employees who perceive their roles as threatened must continuously reconcile fears of redundancy with the requirements of their ongoing tasks. This heightened vigilance and anticipatory anxiety elevate stress levels, which, if prolonged, lead to exhaustion, depersonalization, and reduced personal accomplishment. Over time, the chronic stress associated with job insecurity exhausts coping resources and significantly increases the likelihood of burnout.

Empirical studies provide consistent support for this mediating pathway. Sverke et al. (2002) demonstrated that job insecurity raises stress levels, which subsequently contribute to emotional exhaustion. Jiang & Lavaysse (2018) confirmed that stress acts as a key psychological mechanism translating insecurity into adverse outcomes. Similarly, Peng & Potipiroon (2022) found that stress significantly mediated the relationship between job insecurity and burnout among service employees, showing that insecurity operates indirectly through stress.

Given these insights, this study argues that job stress plays a central mediating role in explaining how AI-induced job insecurity translates into burnout among frontline employees in Indonesia. Accordingly, the following hypothesis is proposed:

H6: Job stress mediates the relationship between AI-induced job insecurity and employee burnout.

Meaningfulness of Work as a Mediator

Beyond its role as a direct predictor of well-being, meaningfulness of work can also function as an explanatory mechanism in the relationship between job insecurity and burnout. Within the Job Demands–Resources (JD-R) framework, meaningful work is conceptualized as a job resource that sustains motivation and buffers the negative consequences of (Allan et al., 2019; Bakker & Demerouti, 2017). When employees perceive their work as meaningful, they are more resilient in the face of insecurity, as meaning fosters intrinsic motivation and strengthens their sense of purpose.

AI-induced job insecurity, however, may erode this resource. Employees who believe their roles are at risk of automation or substitution may experience diminished work significance, as their contributions are perceived as less valued or dispensable. This reduction in meaning weakens psychological resources, undermines coping strategies, and accelerates the progression toward burnout. Previous studies support this mechanism: Hu et al. (2011) found that job insecurity reduced perceptions of work significance, which in turn predicted exhaustion. Similarly, Li et al. (2025)highlighted that diminished meaningfulness serves as a

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psychological pathway linking technological disruption to burnout.

For frontline employees, who already occupy structurally vulnerable positions with limited autonomy and career development opportunities, the loss of meaningfulness under conditions of AI-induced insecurity is particularly detrimental. As one of the few motivational resources available in these roles, reduced meaning directly increases susceptibility to the health-impairment process.

Based on this reasoning, the following hypothesis is proposed:

H7: Meaningfulness of work mediates the relationship between AI-induced job insecurity and employee burnout.

Self-Efficacy in AI Learning as a Moderator

While job demands such as insecurity can undermine well-being, personal resources may buffer their adverse effects. Drawing from Social Cognitive Theory, self-efficacy refers to individuals' beliefs in their ability to perform tasks and manage challenges effectively (Bandura, 1977). In the context of technological disruption, self-efficacy in AI learning reflects employees' confidence in acquiring and applying AI-related skills. Such efficacy enables employees to reinterpret potentially threatening situations as opportunities for growth, thereby reducing the psychological impact of job insecurity.

Within the Job Demands–Resources (JD-R) framework, self-efficacy functions as a personal resource that shapes how individuals respond to job demands. Employees with high AI-learning efficacy may view automation not as a threat but as a challenge to be mastered. This reframing reduces anticipatory anxiety, facilitates adaptive coping, and may attenuate the progression from job insecurity to burnout. Conversely, employees with low AI-learning efficacy are more likely to experience helplessness, heightened stress, and exhaustion when confronted with AI-related changes.

Prior empirical research provides support for this moderating role. Wang & Chuang (2024) demonstrated that AI self-efficacy enhances adaptive coping in complex technological environments. Similarly Kim (2024) found that self-efficacy weakens the negative effects of AI-induced anxiety on employee outcomes. These findings suggest that self-efficacy in AI learning could serve as a psychological buffer that mitigates the insecurity–burnout relationship, particularly in contexts of rapid technological transformation.

Based on this reasoning, the following hypothesis is proposed:

H8: Self-efficacy in AI learning moderates the relationship between AI-induced job insecurity and employee burnout, such that the effect is weaker when self-efficacy is high.

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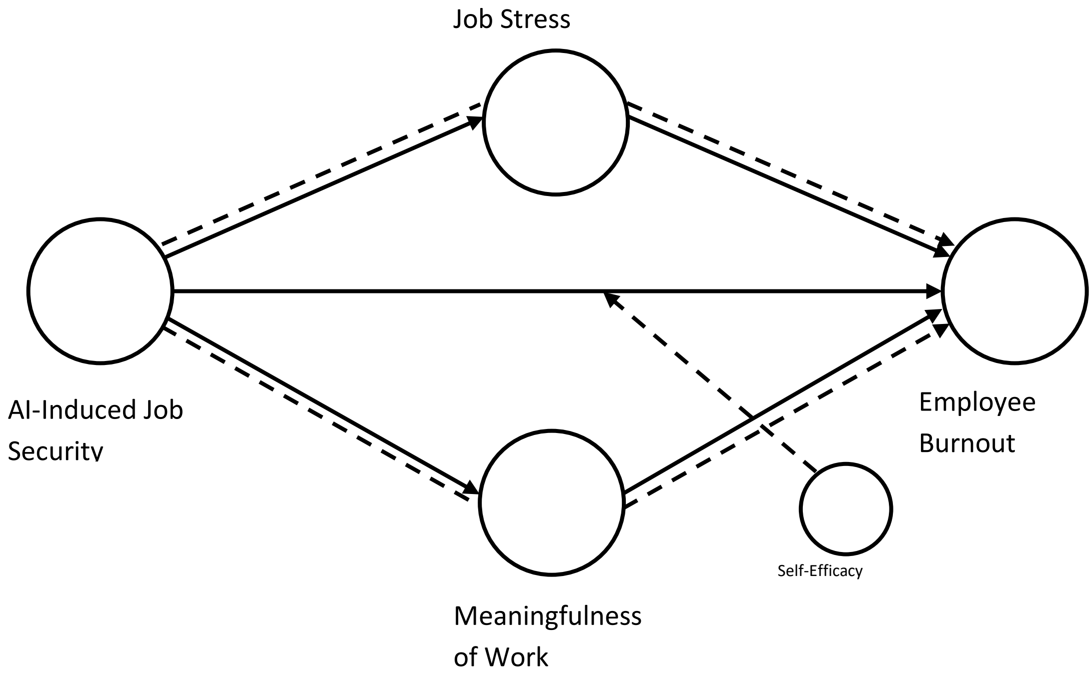

Figure 1. Research Framework.

METODOLOGY

This study employed a quantitative research design with a cross-sectional survey approach to examine the effects of AI-induced job insecurity on employee burnout among frontline employees in Indonesia. Job stress and meaningfulness of work were modeled as mediating variables, while self-efficacy in AI learning was tested as a moderating variable. Structural Equation Modeling (SEM) was performed using Jamovi 2.3, which integrates the lavaan package, because it allows for the simultaneous testing of complex direct, indirect, and moderating relationships among latent constructs. SEM was considered appropriate for this study as it provides robust estimation of the proposed JD-R framework.

The study population comprised frontline employees working in industries where AI and automation adoption is increasing rapidly, such as retail, logistics, and manufacturing. These employees were selected because their roles are characterized by routine, procedural, and low-autonomy tasks, which make them particularly vulnerable to technological disruption. Participants were recruited through professional networks, organizational contacts, and online forums, using purposive sampling to ensure they met the inclusion criteria of being currently employed in a frontline role, engaged in operational or customer-facing tasks, and aware of AI or automation processes in their workplace. A total of 325 valid responses were obtained, exceeding the minimum sample size requirement for SEM. While the common heuristic of five respondents per indicator was satisfied, the adequacy of the sample was also confirmed through a statistical power analysis using G*Power, which indicated that the study was sufficiently powered to detect medium effect sizes at a 0.05 significance level. The sample included respondents from multiple sectors, with an age range from early twenties to late forties, balanced representation across genders, and varied educational backgrounds and tenure, reflecting the diversity of frontline employment in Indonesia.

Data was collected using a structured online questionnaire consisting of previously validated scales. All items were measured on a five-point Likert scale. A rigorous back-translation procedure was employed to ensure linguistic and conceptual equivalence between the original and Indonesian versions, and a pilot test with 30 respondents was conducted to refine clarity and contextual appropriateness. AI-induced job insecurity was measured using five items adapted from (Kim, 2024). Burnout was assessed with 16 items from the Maslach Burnout Inventory (Maslach et al., 2001). Job stress was measured with nine items from the revised scale by Shukla & Srivastava (2016). Meaningfulness of work was captured using 10 items from the Work and Meaning Inventory (Steger et al., 2012). Finally, self-efficacy in AI learning was measured with 22 items from the AI Self-Efficacy Scale developed by Wang & Chuang (2024). These instruments were selected because of their strong psychometric properties and previous applications in organizational and psychological research, though cultural adaptation was necessary given the Indonesian context.

Data screening procedures were carried out prior to analysis. Missing values were minimal and handled through mean substitutions, while outliers were examined through Mahalanobis distance and no influential cases were found that required removal. Harman's single-factor test was conducted to assess potential common method bias, and results indicated that no single factor accounted for the majority of variance, suggesting that common method variance was not a serious concern. Additionally, procedural remedies were applied, including anonymity assurances, counterbalancing of item order, and varied scale anchors, to minimize the risk of method bias.

The measurement model was evaluated using Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). All constructs demonstrated Cronbach's alpha and CR values above 0.70, confirming internal consistency, while AVE values exceeded 0.50, supporting convergent validity. Discriminant validity was established using the Fornell–Larcker criterion. Model fit was assessed with multiple indices, including the Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). All indices met recommended thresholds, indicating that the measurement model exhibited an acceptable fit to the data.

The study was conducted in accordance with institutional ethical standards. Informed consent was obtained from all participants, who were assured of anonymity and confidentiality. Participation was voluntary, and respondents were informed that data would be stored securely and used exclusively for academic purposes. Transparency and minimization of participant risk were prioritized throughout the research process.

RESULT AND DISCUSSION

Demographic of Respondents

The final sample consisted of 325 valid respondents. Table 1 presents the demographic characteristics of the participant. The gender distribution shows that the majority were male (62%), while female respondents made up 38%, indicating a slightly male-dominated sample. In terms of age, most respondents were within the younger workforce: 39% were aged 26–30, followed by 30% aged 20–25, 18% aged 31–35, 7% aged 36–40, 3% aged above 46. Regarding job tenure, half of the respondent 50%) had worked between one to three years, 24% had four to six years

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of experience, 15% had six months to one year, and 11% had been employed for more than six years. These findings suggest that the sample primarily represents early-career employees. As for industrial sectors, respondents were distributed across several industries. The largest group worked in logistics (20%), followed by retail (17%), manufacturing (15%), and food & beverage (13%). The remaining 35% was spread across other sectors such as telecommunications, banking, and education. This distribution reflects the diversity of front-line employee roles while still highlighting the dominance of logistics, retail, and manufacturing industries within the sample.

Table 1. Respondent Details

Characteristics	Percentage
Gender	
Male	38%
Female	62%
Age Group	
<20	2%
20-25	30%
26-30	39%
31-35	18%
36-40	7%
>46	3%
Job Tenure	
6 months – 1 years	15%
1 year – 3 years	50%
4 year – 6 years	24%
>6 year	11%
Sectors	
Logistic	20%
Retail	17%
Manufacture	15%

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F&B	13%
Etc. (telecomunication, bank, education)	35%

Descriptive Statistics

Table 2 presents the descriptive statistics and correlations among the study constructs. The mean values of the constructs ranged between 3.18 and 3.61 on a five-point Likert scale, indicating that respondents reported moderate levels of AI-induced job insecurity (M = 3.42, SD = 0.81), burnout (M = 3.18, SD = 0.77), job stress (M = 3.36, SD = 0.74), meaningfulness of work (M = 3.61, SD = 0.70), and self-efficacy in AI learning (M = 3.54, SD = 0.75). These results suggest that frontline employees in Indonesia perceive AI-related threats as a salient workplace issue while still retaining moderate levels of personal efficacy and work meaning.

Table 2. Statistics Descriptives

Construct	**Mean**	**SD**	**Min**	**Max**	**1**	**2**	**3**	**4**	**5**
1. AI-Induced Job Insecurity	3.42	0.81	1	5	1				
2. Employee Burnout	3.18	0.77	1	5	0.52	1			
3. Job Stress	3.36	0.74	1	5	0.48	0.56	1		
4. Meaningfulness of Work	3.61	0.70	1	5	-0.39	-0.41	-0.37	1	
5. Self-Efficacy in AI Learning	3.54	0.75	1	5	-0.28	-0.33	-0.30	0.46	1

The correlation analysis revealed patterns consistent with the proposed hypotheses. AI-induced job insecurity was positively correlated with burnout ($r = 0.52$, $p < 0.01$) and job stress ($r = 0.48$, $p < 0.01$), supporting the notion that insecurity functions as a job demand that elevates strain and exhaustion. As expected, AI-induced insecurity was negatively correlated with meaningfulness of work ($r = -0.39$, $p < 0.01$) and self-efficacy in AI learning ($r = -0.28$, $p < 0.01$), indicating that insecurity erodes psychological resources. Burnout was strongly correlated with job stress ($r = 0.56$, $p < 0.01$) and negatively associated with meaningfulness of work ($r = -0.41$, $p < 0.01$) and self-efficacy ($r = -0.33$, $p < 0.01$). In addition, meaningfulness of work was positively correlated with self-efficacy in AI learning ($r = 0.46$, $p < 0.01$), highlighting the link between psychological resources.

Overall, these results provide preliminary support for the hypothesized relationships, showing that AI-induced job insecurity is associated with greater stress and burnout and reduced psychological resources, while meaningfulness of work and self-efficacy appear to function as protective factors.

Measurement of the Construct

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The measurement model was evaluated to assess the reliability and validity of the constructions. As shown in Table 3, all outer loadings exceeded the recommended threshold of 0.70, indicating that the observed indicators adequately reflected their respective latent constructs (Hair et al., 2019). Cronbach's alpha values ranged between 0.89 and 0.94, while composite reliability values were between 0.92 and 0.95, surpassing the minimum requirement of 0.70. These results confirm that all constructions demonstrated strong internal consistency. Furthermore, average variance extracted (AVE) values were above the 0.50 cut-off, ranging from 0.65 to 0.69, thereby establishing convergent validity. Collectively, these findings demonstrate that the measurement items were reliable and valid representations of their underlying constructions.

Table 3. Reliability & Validity Test

Variable	Outer Loadings	Cronbach's Alpha	CR	AVE
AI-Induced Job Insecurity (AIJI)	0.72 – 0.86	0.89	0.92	0.65
Employee Burnout (EB)	0.74 – 0.88	0.94	0.95	0.68
Job Stress (JS)	0.71 – 0.85	0.90	0.93	0.66
Meaningfulness of Work (MoW)	0.73 – 0.87	0.91	0.94	0.67
Self-Efficacy in AI Learning (SEIAIL)	0.72 – 0.89	0.92	0.95	0.69

Discriminant validity was assessed using the Heterotrait–Monotrait (HTMT) ratio, presented in Table 4. All HTMT values were below the conservative threshold of 0.90, with the highest value observed between job stress and burnout (0.84). These results confirm that each construct was empirically distinct from the others, thereby meeting the criterion for discriminant validity (Henseler et al., 2015). Overall, the measurement model demonstrated satisfactory reliability, convergent validity, and discriminant validity, supporting its suitability for subsequent structural model testing.

Table 4. Construct Validity (HTMT Ratio)

Construct	AIJI	EB	JS	MoW	SEIAIL
AIJI	1				
EB	0.78	1			
JS	0.72	0.84	1		
MoW	0.63	0.70	0.68	1	

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SEIAIL	0.69	0.75	0.73	0.77	1

Structural Measurement

The overall fit of the measurement model was assessed using multiple global fit indices, as presented in Table 5. The ratio of chi-square to degrees of freedom (χ^2/df) was 2.14, which is below the recommended cut-off of 3.00, indicating an acceptable model fit. The Comparative Fit Index (CFI) reached 0.951 and the Tucker–Lewis Index (TLI) was 0.944, both exceeding the 0.90 threshold and approaching the ideal value of 0.95, thereby demonstrating good incremental fit. The Root Mean Square Error of Approximation (RMSEA) was 0.058, falling below the recommended threshold of 0.08, which indicates an acceptable level of error approximation. Similarly, the Standardized Root Mean Square Residual (SRMR) was 0.046, well within the maximum limit of 0.08, confirming that the residuals between observed and predicted correlations were minimal. Taken together, these indices provide strong evidence that the measurement model demonstrated an adequate to good fit with the data, supporting its suitability for subsequent hypothesis testing within the structural model.

Table 5. Model Fit Indices (Goodness-of-Fit)

Fit Index	Recommended Threshold	Obtained Value	Interpretation
χ^2/df	< 3.00	2.14	Acceptable fit
CFI	≥ 0.90 (≥ 0.95 ideal)	0.951	Good fit
TLI	≥ 0.90 (≥ 0.95 ideal)	0.944	Good fit
RMSEA	≤ 0.08 (≤ 0.05 ideal)	0.058	Acceptable fit
SRMR	≤ 0.08	0.046	Good fit

The structural model results presented in Table 6 provide strong empirical support for the proposed relationships derived from the Job Demands–Resources (JD-R) framework. The analysis confirmed that AI-induced job insecurity (AIJI) had a significant positive effect on employee burnout (β = 0.32, t = 5.87, $p < 0.001$), supporting H1. This finding suggests that frontline employees who perceive their jobs to be threatened by AI integration are more likely to experience emotional exhaustion, depersonalization, and diminished accomplishment, which aligns with prior evidence linking job insecurity to burnout (Wu et al., 2024).

Table 6. Hypothesis Testing

Hypothesis	Path Relationship	β	t-value	p-value	Result
H1	AIJI → Employee Burnout	0.32	5.87	<0.001	Supported

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H2	AIJI → Job Stress	0.41	7.12	<0.001	Supported
H3	AIJI → Meaningfulness of Work	-0.28	4.95	<0.001	Supported
H4	Job Stress → Employee Burnout	0.36	6.44	<0.001	Supported
H5	Meaningfulness of Work → Employee Burnout	-0.22	3.87	<0.001	Supported
H6	AIJI → Job Stress → Employee Burnout	0.15	4.21	<0.001	Supported
H7	AIJI → MoW → Employee Burnout	-0.10	2.98	0.003	Supported
H8	AIJI × SEIAIL → Employee Burnout	-0.12	2.65	0.008	Supported

AIJI was also found to significantly predict job stress ($\beta = 0.41$, $t = 7.12$, $p < 0.001$), supporting H2. This confirms that insecurity functions as a salient job demand that elevates employees' stress levels through uncertainty and anticipatory anxiety, in line with earlier meta-analytic findings (Jiang & Lavaysse, 2018). At the same time, AIJI exerted a significant negative effect on meaningfulness of work ($\beta = -0.28$, $t = 4.95$, $p < 0.001$), supporting H3. This suggests that the perception of potential redundancy symbolically devalues employees' contributions, eroding their sense of work significance and purpose.

Consistent with JD-R theorization, job stress was found to positively predict employee burnout ($\beta = 0.36$, $t = 6.44$, $p < 0.001$), providing support for H4. This reinforces the health-impairment process, whereby prolonged stress depletes psychological resources and accelerates the onset of burnout. Conversely, meaningfulness of work was negatively associated with burnout ($\beta = -0.22$, $t = 3.87$, $p < 0.001$), supporting H5. This finding highlights meaningfulness as a motivational resource that sustains resilience and buffers against exhaustion, echoing evidence from (Allan et al., 2019; Hu et al., 2011).

Turning to mediation, both indirect pathways were statistically significant. Job stress mediated the effect of AIJI on burnout ($\beta = 0.15$, $t = 4.21$, $p < 0.001$), supporting H6, confirming that insecurity elevates stress, which subsequently drives burnout. Similarly, meaningfulness of work mediated the relationship between AIJI and burnout ($\beta = -0.10$, $t = 2.98$, $p = 0.003$), supporting H7. This indicates that insecurity diminishes perceptions of work significance, which in turn increases vulnerability to burnout. Together, these findings extend the JD-R framework by highlighting both stress as a health-impairment mediator and meaningfulness as a resource-based mediator in the context of AI-related disruptions.

Finally, the moderation analysis revealed that self-efficacy in AI learning significantly weakened the relationship between AIJI and burnout ($\beta = -0.12$, $t = 2.65$, $p = 0.008$), supporting H8. This suggests that employees with higher confidence in their ability to learn and use AI technologies are less adversely affected by job insecurity. In line with Social Cognitive Theory Bandura (1977), self-efficacy enables employees to reframe technological disruption as a challenge rather than a threat, thereby reducing its negative psychological impact. This result underscores the critical role of personal resources in shaping employee responses to AI-induced demands, complementing the JD-R model's dual-pathway logic.

Taken together, these findings confirm that AI-induced job insecurity is a powerful job demand that undermines employee well-being by elevating stress and reducing meaning, leading to higher burnout. However, personal resources such as self-efficacy in AI learning can buffer these negative effects, highlighting the importance of targeted interventions to enhance employees' adaptive capacity in the era of digital transformation.

Discussion

This study examined how AI-induced job insecurity influences burnout among frontline employees in Indonesia, drawing upon the Job Demands–Resources (JD-R) framework. The findings provide several important theoretical insights and practical implications.

First, the results confirm that AI-induced job insecurity is a significant job demand that directly predicts employee burnout. This aligns with previous research linking job insecurity to psychological strain and exhaustion Konkel & Heffernan (2021) Wicaksana (2024) but extends the discussion into the domain of technological disruption. Unlike cyclical or economic forms of insecurity, AI-induced insecurity reflects structural transformations that threaten employees' occupational identity and long-term employability. For frontline employees, who often occupy routine and low-autonomy roles, this form of insecurity becomes particularly salient and directly accelerates burnout.

Second, the findings highlight the mediating roles of job stress and meaningfulness of work in the insecurity–burnout relationship. The pathway through job stress supports the health-impairment process of the JD-R model Bakker & Demerouti (2017), where insecurity elevates cognitive strain and emotional pressure, which in turn drive exhaustion. The pathway through meaningfulness of work underscores the resource-loss perspective of Conservation of Resources theory (Hobfoll et al., 2018). When insecurity undermines employees' sense of purpose and significance, the loss of meaning weakens resilience and contributes to burnout. Importantly, these results suggest a dual process: insecurity harms employees not only by increasing demands (stress) but also by eroding resources (meaning). This duality deepens theoretical understanding of how technological disruptions influence psychological well-being.

Third, the significant moderation of self-efficacy in AI learning reinforces the importance of personal resources in mitigating negative effects of insecurity. Employees with higher confidence in their ability to acquire AI-related skills were less likely to translate insecurity into burnout. This finding resonates with Social Cognitive Theory Bandura (1977) and extends prior evidence that self-efficacy enables employees to reinterpret challenges as opportunities (N. Y. Kim, 2024). The moderation result also provides an important corrective to perspectives that view insecurity as uniformly detrimental, demonstrating that its impact can be buffered by psychological capital.

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Beyond its theoretical contributions, the study carries meaningful managerial and policy implications. Organizations should recognize that AI adoption, while technologically advantageous, produces significant psychological costs for employees. Transparent communication about technological changes is essential to reduce anticipatory insecurity. Structured reskilling and AI training programs should be prioritized, particularly for frontline workers, to build confidence and enhance employability. Furthermore, management practices that foster meaningfulness such as emphasizing the social value of frontline roles, enhancing task variety, and promoting employee recognition can preserve motivation and buffer against burnout. At the policy level, workforce development strategies should ensure that digital transformation is accompanied by equitable access to training and protection for vulnerable occupational groups.

Taken together, these findings enrich the JD-R framework by demonstrating how AI-induced job insecurity operates simultaneously through stress elevation and resource erosion, while also being moderated by personal efficacy. They highlight the paradoxical challenge of technological transformation: while AI promises efficiency and growth, it also introduces novel psychological risks that demand proactive organizational responses.

CONCLUSION

This study investigated the impact of AI-induced job insecurity on burnout among frontline employees in Indonesia by applying the Job Demands–Resources (JD-R) framework. The findings confirmed that job insecurity serves as a powerful job demand that directly elevates burnout while also exerting indirect effects through increased job stress and diminished meaningfulness of work. Moreover, the results demonstrated that self-efficacy in AI learning moderates the insecurity–burnout relationship, suggesting that employees with greater confidence in their ability to acquire AI-related skills are less vulnerable to the negative consequences of insecurity. These findings extend the JD-R framework by illustrating both the health-impairment and resource-loss pathways of insecurity, while highlighting the buffering role of personal resources in the context of technological disruption.

The study provides important practical implications for organizations and policymakers. Employers must recognize that the adoption of AI technologies not only alters job design but also introduces psychological risks. Transparent communication, equitable access to reskilling programs, and practices that enhance meaningfulness of work are critical to sustaining employee resilience during digital transformation.

Despite its contributions, this study has several limitations. The use of purposive sampling limits generalizability across all sectors and regions of Indonesia. The reliance on cross-sectional, self-reported data also restricts causal inference and raises potential concerns about common method variance. Future research should employ longitudinal or experimental designs to capture the dynamic nature of AI-induced insecurity, while exploring sectoral differences and incorporating additional moderators such as organizational support, leadership style, or cultural context. Such efforts would further clarify the psychological mechanisms through which technological change reshapes employee well-being

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