

Artificial Intelligence, Job Insecurity and Employee Adaptation: A JD-R Model Perspective

Dr. Bharti Sujan,

HOD, Gandhi Memorial National College,
Ambala Cantt.

Dr. Disha Arora,

Assistant Professor, Gandhi Memorial National College,
Ambala Cantt.

Ms. Kamalpreet Kaur,

Assistant Professor, Gandhi Memorial National College,
Ambala Cantt.

This study investigates the impact of artificial intelligence (AI) integration on employee job insecurity and its associated psychological and behavioral consequences. Grounded in the Job Demands–Resources model and resource protection theory, the research examines three dimensions of job insecurity—job holding, wage/promotion, and excessive competition insecurity—to understand how employees perceive threats emerging from AI-driven workplace transformations. Using data from 384 employees and employing exploratory factor analysis, reliability testing, correlations, and regression modelling, the study reveals a strong negative relationship between AI adaptation and job insecurity, indicating that employees who adapt more effectively to AI experience reduced insecurity. The findings further highlight tech-learning anxiety as a key mechanism through which AI-related uncertainty affects employee well-being and performance. Importantly, vocational learning ability and mindfulness emerge as significant buffering factors that mitigate these adverse effects. The study emphasizes the need for organizations to build supportive learning environments and develop interventions that strengthen employee resilience in AI-enabled work settings.

Keywords: Artificial Intelligence, Job Insecurity, Tech-Learning Anxiety, Vocational Learning Ability, Mindfulness

Introduction

The industries that rely significantly on repetitive operations (such as radiology and transportation), artificial intelligence is causing a shift in the way individuals perform their jobs. According to Dafoe et al. (2021), artificial intelligence may not be able to completely replace radiologists; nonetheless, those radiologists who are able to make efficient use of AI will continue to be relevant. This is a reflection of the larger trend of human-artificial intelligence collaboration (HAI-C), in which workers employ AI as a tool to boost their productivity rather than being replaced by it. Nonetheless, employees frequently express concerns on the instability of their jobs in the HAI-C sector, namely the fear that their capacity to effectively collaborate with AI will have an influence on their employment continuity. One of the factors that can contribute to feelings of powerlessness and risks to job security is the fact that artificial intelligence systems are constantly changing, invisible, and difficult to understand (Anthony et al., 2023). Probst's (2002) framework of job insecurity is utilized in this article. This framework establishes a connection between technological advancement and job insecurity, and it also influences attitudes and emotional responses related to the workplace, such as worry. According to the concept, the beliefs of employees regarding the threat that artificial intelligence poses to their job continuity can have substantial emotional and cognitive effects. One example of this is tech-learning anxiety, which refers to the tension that is associated with learning how to effectively use AI. According to the Job Demands–Resources (JD-R) model, HAI-C job insecurity is categorized as a hindrance demand. This type of demand demands continuous effort and has the potential to negatively impact employee cognition, job performance, and overall well-being. This includes how stress brought on by artificial intelligence influences creative actions and informal learning practices in the workplace. The transition from viewing artificial intelligence (AI) as a basic tool to viewing it as a cooperater in the workplace is necessary in order to comprehend human-AI collaboration. Due to this, the stakes are raised for employees, as they are required to properly interact with artificial intelligence (AI) rather than simply using it in order to continue to be relevant in the workplace. According to the

findings of the research, artificial intelligence (AI) has the potential to boost creativity and improve job efficiency; yet, employees frequently feel tech-learning anxiety, which is a specific type of anxiety that pertains to learning to work alongside AI. This is not the same as earlier concerns on the possibility of being replaced by artificial intelligence; rather, it is about developing the appropriate abilities to work with AI. Impact of Artificial Intelligence on Work and Life Quality highlights the fact that worry over learning new technologies, which originates from HAI-C job instability, can have an effect on both work and life quality. When it comes to the workplace, this concern might have a negative impact on creative performance and informal learning practices. This is because people may have difficulty developing the skills necessary to interact with artificial intelligence. Additionally, the research investigates the impact of anxiety regarding technology-based learning on psychological health (mental, physical, and social well-being) as well as life well-being (subjective pleasure and satisfaction and overall happiness). Work-related outcomes and personal life satisfaction can both suffer when there is a high level of worry around the collaboration of AI. One of the most important contributions made by the study is that it has demonstrated that mindfulness can serve as an efficient buffer to mitigate the adverse effects of HAI-C job instability and anxiety related to technology learning. As a personal resource, mindfulness assists employees in managing stress, improving their ability to self-regulate, and cultivating emotional equilibrium in reaction to the uncertainties that are triggered by artificial intelligence. Workers who practice mindfulness are able to concentrate on the here and now and better adjust to the shifting terrain of artificial intelligence collaboration. This enables them to feel more competent of dealing with the demands that are associated with AI and reduces their anxiety. This research extends the application of the JD-R model to the specific setting of human-AI collaboration, thereby providing fresh insights into the ways in which technology innovations effect job insecurity. The study places more of an emphasis on human-AI collaboration and job insecurity than it does on employment instability that is just associated with the deployment of AI. As a result of this contrast, the focus moves from the anxiety about being replaced by artificial intelligence to the anxiety about successful collaboration with AI. In addition, the study identifies tech-learning anxiety as a primary method via which HAI-C job instability has an effect on employees. Additionally, it offers a scale to assess this worry, which contributes to a better understanding of how the use of learning technology affects the job performance and well-being of employees. The research provides organizations with practical solutions to mitigate the negative effects of anxiety caused by artificial intelligence (AI), thereby increasing the level of pleasure that people have in both their work and their personal lives. Mindfulness is identified as a crucial mitigating component in the research. It is important for businesses to acknowledge the mental and emotional strains that are placed on employees as a result of workplace collaboration with AI. In order to assist employees in navigating the problems that come with working with artificial intelligence, it may be beneficial to provide training programs, cultivate a learning atmosphere that is supportive, and incorporate mindfulness techniques. By cultivating a mindful workplace, firms can assist their employees in managing anxiety, concentrating on the here and now, and improving their ability to collaborate with artificial intelligence, so enhancing the performance of both individuals and the organization as a whole. Specifically, the research sheds light on the ever-changing nature of human-AI collaboration as well as the possible employment insecurity that comes along with an evolving nature. There is a possibility that employees will confront new hurdles in relation to their capacity to effectively engage with AI systems as artificial intelligence becomes more incorporated into workplaces. However, employers have the ability to minimize these issues by offering the appropriate resources, such as training, mindfulness programs, and supportive work environments, in order to assist with the development of the essential abilities and the reduction of anxiety among their employees. Understanding and resolving the issue of human-AI collaboration with job security is essential for ensuring that a workforce that is healthy, engaged, and driven continues to exist.

Review of literature and Hypothesis Development

The purpose of this study is to give a complete investigation into the impact that artificial intelligence (AI) has on job insecurity as well as the potential psychological repercussions that it may have on employees. The most important topics that were covered were to the ways in which artificial intelligence (AI) presents new difficulties to the workforce, which can result in fear, insecurity, and behavioral changes among workers, particularly in situations where businesses are unable to properly manage these changes. A summary of the most important ideas that were discussed is as follows:

Impact of Artificial Intelligence on Employment: According to Ford (2015), who makes the argument that the employment impact of artificial intelligence would be more extensive, strong, and long-lasting than that of earlier technological revolutions, the passage makes reference to Ford. According to Frey and Osborne (2017), artificial

intelligence is ready to revolutionize a wide range of industries, including sectors such as finance, accounting, and senior management. These are all areas where positions that require a lot of mental effort and are financially lucrative might potentially be replaced by AI systems. According to the resource protection model developed by Hobfoll (1989), feelings of stress are triggered whenever external factors, such as the advent of artificial intelligence (AI), pose a threat to the resources that employees rely on (for example, job stability and career prospects). Employees frequently make an effort to preserve the status quo, and when they believe that they have little ability to do so, it leads to a sense of fear over their employment security. It is especially troubling that artificial intelligence has the potential to replace occupations because it does not only target jobs that require low levels of ability and manual labor, but also jobs that require high levels of cognitive abilities and attract big incomes. This signifies a fundamental shift in the way that artificial intelligence influences a variety of businesses and the perception of job security that individuals have.

Job insecurity and the dangers posed by external technological developments

In the beginning, Greenhalgh and Rosenblatt (1984) defined work insecurity as the emotional and psychological state that employees go through when they perceive threats to the continuity of their employment. As a result of the intervention of artificial intelligence (AI) and other new technologies in businesses, employees frequently experience anxiety and panic because they are concerned about the future of their roles and the stability of their jobs. New technologies, such as artificial intelligence, are regarded as an external influence that can have an effect on the stability of individuals' work lives. It is possible for employees to have increased levels of anxiety when firms fail to appropriately handle technology advances. This can have a detrimental influence on employees' performance, contentment, and even their emotional well-being. Hoffoll's Resource Protection Model, which was published in 1989, draws attention to the influence that stress has on job insecurity. As a result of these threats, employees may experience increased anxiety because they perceive ambiguity over their access to resources (such as promotions, job continuity, and salary), or they perceive that they are unable to defend those resources, which contributes to job insecurity. In a different model, titled Five-Dimensional Job Insecurity, Hu Sanman and Li Zhongbin (2010) conceptualized employee job insecurity in Chinese enterprises within a five-dimensional structure. This structure includes Job Holding Insecurity, which refers to the fear of losing one's job; Job Performance Insecurity, which is concerned with the fear of not being able to meet performance expectations; and Pay Promotion Insecurity, which emphasizes the fear of stagnation in compensation and career advancement. Insecurity brought on by excessive competition is yet another aspect that contributes. Anxiety that emerges as a consequence of greater rivalry for roles as a consequence of technical advancements, which further results in interpersonal insecurity. The concerns that are associated with the relationships with coworkers or management. The Influence of Artificial Intelligence on Job Insecurity: In this context, the impact that artificial intelligence has on employment is far-reaching and has the potential to result in changes to the structure of employment as well as a decrease in the pay of workers. It is possible that artificial intelligence technologies could raise competitiveness and contribute to pay promotion insecurity. This is because automation and AI may lessen the demand for some roles, which would result in a higher level of rivalry for the positions that are still available. In addition, the study sheds insight on the influence that AI has on several aspects of job security. The use of artificial intelligence (AI) to automate processes that were previously performed by people may result in job displacement, which in turn causes employees to be concerned about the possibility of losing their positions. It is possible that employees would face uncertainty regarding their pay and promotions as a result of the reduction in the number of accessible roles brought about by artificial intelligence (AI). This is because the demand for specific jobs may decrease, which will result in fewer prospects for career advancement. The developments that are driven by artificial intelligence could result in more competition for fewer roles, particularly in industries that are being influenced by automation. In an increasingly AI-driven workplace, employees may be concerned that their qualifications and performance may not be sufficient to distinguish themselves from the competition. The research proposes that vocational learning ability, which refers to the capacity of employees to adapt, acquire new skills, and evolve in response to the adjustments brought about by artificial intelligence, may operate as a moderating element in the manner in which employees perceive job insecurity. Because they are more equipped to learn new skills, improve their employability, and participate in the collaborative human-AI models that enterprises may adopt, individuals who have superior learning abilities may be less harmed by the pressures associated with the deployment of artificial intelligence.

Psychological influence of Artificial Intelligence on Job Insecurity

The psychological influence of AI on job insecurity is investigated by focusing on the ways in which learning ability might lessen the negative emotional and behavioral responses to job insecurity, including anxiety. It is likely that employees who have a higher level of self-assurance in their capacity to acquire new abilities will suffer less fear and insecurity regarding their employment prospects in an atmosphere that is driven by artificial intelligence. The purpose of the research presented in this paper is to get an understanding of the effects that artificial intelligence and job insecurity have on employees. More specifically, the research investigates how job holding insecurity, wage promotion insecurity, and excessive competition insecurity influence the psychological well-being and conduct of personnel. In addition to this, it intends to investigate the role that the capacity for vocational learning can play as a buffer to reduce the impact of these adverse impacts.

Hypothesis:

H1a: The implementation of artificial intelligence in workplaces has the potential to considerably raise job insecurity across a variety of dimensions.

Objectives of the Study

To comprehend the integration of artificial intelligence in professional environments and its effect on employment insecurity.

To comprehend the perception of enough information concerning AI's role in the workplace and its effect on job security.

Data Analysis & Interpretation

The analysis of data was conducted initially by examining the profiles of the responding employees and subsequently to explore the relationship between adaptation of Artificial Intelligence and Job Insecurity amongst employees. Various statistical tools have been employed, including descriptive and inferential statistics, along with the application of multiple regression techniques to evaluate the dependency relationships among several variables (Hair et al., 2008; Hooper et al., 2008). This study begins with the estimation of the measurement model to confirm scale uni-dimensionality, reliability, and validity. The scales have undergone assessments of reliability, including Cronbach's alpha, as well as evaluations of nomological and face validity. The subsequent step involves employing a regression model to evaluate the relationships among latent variables. Inquiry is not merely about gathering data and statistics. The data presented serves as a foundation for constructing an empirical model, allowing for the careful elucidation of relationships and the derivation of significant conclusions.

Providing a clear and comprehensive overview of the data is the objective of descriptive statistics. This is accomplished without drawing any predictions or judgments about a wider population. It is helpful for spotting trends or patterns before undertaking more advanced analysis, as well as for summarizing enormous sets of data. The full descriptive analysis for the scales on mapping Job Holding Insecurity; Wage/Promotion Insecurity; Excessive Competition Insecurity and its impact on adaptation of AI amongst employees. Several aspects were examined in order to gain a better understanding of the influence that the aforementioned problems have posed

Table No 1: Descriptive Statistics

	N	Min	Max	Sum	Mean		Std. Deviation
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic
Job Holding Insecurity	384	1	5	740	1.93	.029	0.576
Wage/ Promotion Insecurity	384	1	5	854	2.22	.020	0.409
Excessive Competition Insecurity	384	1	5	711	1.85	.027	0.54
AI Implementation	384	1	5	773	2.01	.043	0.836

The results of the research make it abundantly clear that the mean values fall somewhere in the range of 1.93 to 2.22, while the standard deviation values ranged from 0.409 (**Job Holding Insecurity**) to 0.836 (for **AI Implementation**). Every single one of the statements had a minimum score that ranged from one to five, correspondingly.

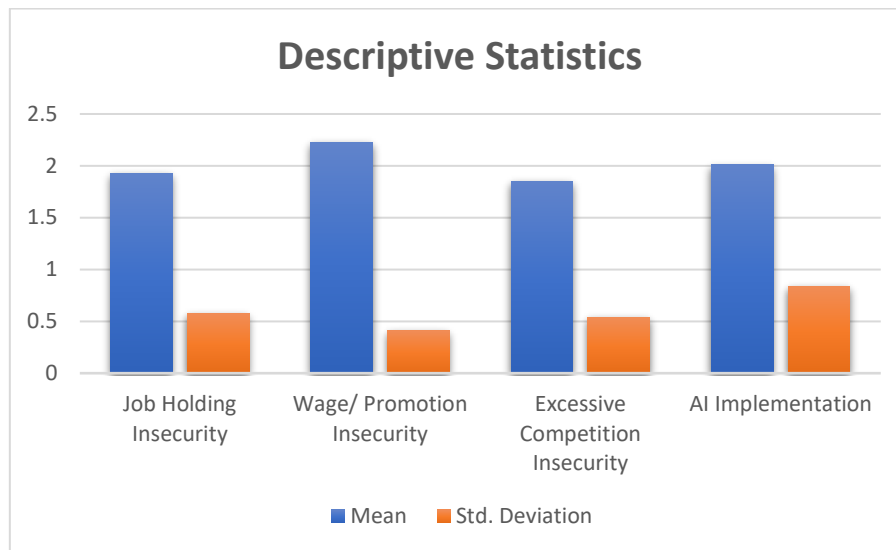


Exhibit 1 Descriptive Statistics

Factorial Validity

The term "factorial validity" describes the degree to which a collection of variables that have been measured accurately reflects the underlying factors or constructs that they are designed to measure. In the context of factor analysis, which is a statistical method that is used to uncover patterns or clusters of related variables in huge datasets, it is frequently evaluated because of its significance. Factorial validity is a method that helps to ensure that the variables in a test or measurement scale are organized in an appropriate manner and that they are measuring the dimensions or factors that were intended to be measured. For a more straightforward explanation, factorial validity is an evaluation that determines whether or not the variables in the instrument genuinely represent the underlying concepts (factors) that they are intended to measure.

The principal component analysis coupled with varimax rotation was utilized in the process of doing the factor analysis. Documentation of a step that was carried out in full as part of the factor analysis process can be seen below. Computing Bartlett's test of sphericity was used to determine whether or not the sampling was enough. The results are summarized in table 2 which can be found below:

Table: 2 KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.779
Bartlett's Test of Sphericity	Approx. Chi-Square	670.84
	Df.	28
	Sig	.000

The table-2 above presents several crucial components of the output: the Kaiser-Meyer-Olkin measure of sampling adequacy and Bartlett's test of sphericity. The KMO statistic ranges from 0 to 1. A value of 0 suggests that the factor analysis may not be suitable. A value approaching 1 suggests that the correlation patterns are relatively concentrated, leading to the expectation that the factor analysis will yield distinct and reliable factors.

Table 3 Job Insecurity: Total Variance Explained

Total Variance Extracted for Job Insecurity: 70.249%			
Items	Components	Items	Components
J11	.661	J17	.786

JI2	.638	JI8	.876
JI3	.810	JI9	.853
JI4	.865	JI10	.887
JI5	.859	JI11	.627
JI6	.893	JI12	.731

Extraction Method: Principal Component Analysis
Rotation Method: Varimax with Kaiser Normalization

Table: 4 KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.885
Bartlett's Test of Sphericity	Approx. Chi-Square	204.727
	Df.	45
	Sig	.000

Table 5 AI Implementation: Total Variance Explained

Total Variance extracted AI Implementation: 70.995%	
Items	Components
AI1	.649
AI2	.763
AI3	.730

Extraction Method: Principal Component Analysis
Rotation Method: Varimax with Kaiser Normalization

Table 2 to table 5 above illustrates many critical components of the output: the Kaiser-Meyer-Olkin measure of sample adequacy and Bartlett's test of sphericity. The KMO statistic ranges from 0 to 1. A value of 0 indicates that the factor analysis is likely to be inappropriate. A score approaching 1 signifies that correlation patterns are relatively concentrated, suggesting that the factor analysis will provide identifiable and dependable factors. KMO and Bartlett's test demonstrates a significant association among some items. Consequently, a substantial Bartlett's Test of Sphericity is necessary (O'Rourke et al., 2013; Malhotra & Birks, 2007). Since $p = 0.000$ (indicating significance below 0.05) for all scales, we may forward with factor analysis. The results of the Exploratory Factor Analysis indicated that the scale was unidimensional. Delgado-Ballester et al. (2003) indicated that utilizing the heuristic of an Eigenvalue exceeding 1, one component was selected, which accounted for 70.995% of the overall variance. Consequently, the exploratory factor analysis on the leadership scale encountered by women produced a singular factor.

Face Validity & Reliability: This pertains to the subjective assessment of whether the questionnaire ostensibly measures what it purports to measure. Although it does not entail statistical testing, it was taken into account during the design phase to ensure the questions are suitable for the intended audience. The reliability of a scale refers to the consistency and stability of the results it produces over time or across different conditions. A reliable scale yields similar results when administered to the same subjects under the same conditions, and its measurements are stable and dependable. To assess internal consistency, the most common measure is **Cronbach's alpha**, where a value between 0.7 and 0.9 is considered reliable.

Table 6 Reliability of the scale

NAME OF THE SCALE	CRONBACH'S ALPHA
Job holding insecurity, ,	0.861
Wage promotion insecurity	0.860
Excessive competition insecurity+	0.831

AI Implementation	0.912
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Hypothesis Testing

Correlations & Regression Model			
		Job Insecurity	AI Implementation
Job Insecurity	Pearson Correlation	1	-.784**
	Sig. (2-tailed)		.000
	N	384	384
AI Implementation	Pearson Correlation	-.784**	1
	Sig. (2-tailed)	.000	
	N	384	384
**. Correlation is significant at the 0.01 level (2-tailed).			

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	-.784 ^a	.614	.611	.521

The correlation between Job Insecurity and AI Implementation is **-0.784**, which is a **strong negative correlation**. This means that as **AI adaptation increases**, **job insecurity tends to decrease**. The significance value is **0.000**, which is less than the standard significance level of **0.01**. Therefore, this correlation is **statistically significant**, suggesting a meaningful relationship between the two variables. **R Square (Coefficient of Determination): 0.614** means that approximately **61.4%** of the variance in **Job Insecurity** can be explained by **AI Adaptation**. This is a relatively strong model, indicating that AI adaptation plays a substantial role in influencing job insecurity. The **Adjusted R Square** value of **0.611** accounts for the number of predictors in the model, providing a more accurate measure. It's very close to the R Square value, indicating that the model does not overfit. The **Std. Error of the Estimate** is **0.521**, which gives an estimate of the average distance between the observed values and the predicted values. Smaller values of this error suggest that the predictions from the model are relatively close to the actual data.

Inference

The negative correlation (-0.784) between AI Adaptation and Job Insecurity indicates that greater AI adoption is associated with lower job insecurity, which might suggest that workers see AI as a tool for enhancing job stability or creating new roles, as opposed to a source of job loss. The regression model explains a significant portion (61.4%) of the variance in job insecurity, indicating that AI adaptation is a strong predictor of job insecurity.

Essential Insights:

The implementation of artificial intelligence (AI) in the workplace may increase job insecurity through various mechanisms. Artificial intelligence thrives in automating monotonous, repetitive tasks. This includes all tasks from data input to fundamental customer service inquiries, which might potentially eradicate the need for human labor in roles primarily including these responsibilities. Workers may be replaced due to artificial intelligence assuming specific jobs or complete roles. This is particularly applicable to employees in positions that are entirely automatable. Artificial intelligence generally necessitates a higher degree of technical proficiency, encompassing skills in programming, data analysis, and machine learning. Workers in professions rendered obsolete by automation may lack the requisite abilities to transition into roles associated with artificial intelligence. This mismatch may hinder workers' ability to adjust to the evolving labor

market, potentially exacerbating job instability. Rather than replacing labor, artificial intelligence techniques are occasionally applied to enhance the productivity of existing employees. AI systems can monitor and assess employee performance in real time, potentially leading to heightened pressure on workers to meet performance standards.

Additional Inquiry: It would be advantageous to examine additional factors (such as employee training, job classification, and industry) that may influence the correlation between AI adaptation and job insecurity.

Model Enhancement: Incorporating additional pertinent variables (e.g., employee perception of AI) into the model may enhance the prediction of job insecurity. AI's extensive influence on employment: AI is anticipated to substantially disrupt labor markets, affecting both high-skill and low-skill positions. Job insecurity encompasses various facets, including apprehensions regarding employment retention, remuneration, competitiveness, and performance.

Learning as a safeguard: The capacity of employees to learn will significantly influence the impact of AI on their job insecurity and psychological health. Organizations ought to focus vocational training programs to assist employees in adapting to the evolving employment market. In conclusion, firms must meticulously manage the psychological effects of AI and technological disruption to mitigate job insecurity. This entails cultivating a culture of perpetual learning and offering assistance to enable people to navigate the hurdles presented by AI.

Conclusion:

The study demonstrates that the integration of artificial intelligence (AI) in workplaces significantly influences employees' perceptions of job insecurity across multiple dimensions, including job holding, wage/promotion opportunities, and competition for roles. Findings show a strong negative relationship between AI adaptation and job insecurity, indicating that employees who successfully adapt to AI experience reduced anxiety and greater stability. Tech-learning anxiety emerges as a critical pathway through which AI-driven changes affect psychological well-being and work-related behaviors. Importantly, vocational learning ability and mindfulness serve as protective resources that help employees navigate uncertainty, improve adaptability, and maintain emotional balance. Overall, the study highlights the need for organizations to view AI not merely as a technological upgrade but as a human-centered transformation requiring support systems that foster continuous learning, resilience, and psychological well-being.

Limitations and Suggestions:

This study is subject to certain limitations that offer opportunities for future research. The cross-sectional design restricts causal interpretation, and the reliance on self-reported data may introduce response bias. Additionally, the sample may not fully represent diverse industries or geographic contexts with varying levels of AI adoption. Future studies should employ longitudinal designs, incorporate a wider range of sectors, and include additional variables such as organizational culture, leadership communication, trust in AI, and digital literacy to enrich understanding. Researchers and practitioners are also encouraged to explore intervention-based approaches—such as AI literacy training, continuous vocational learning programs, and mindfulness-based support—to strengthen employee resilience and reduce job insecurity in AI-driven workplaces.

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