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Artificial Intelligence Adoption and Career Reconfiguration of Office Workers: The Mediating Role of Training and Organizational Support

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Abstract

Background: The development of artificial intelligence (AI) is fundamentally reshaping workforce structures, particularly for office workers whose task profiles are highly exposed to automation-driven transformation. As organizations integrate AI into operational systems, employees increasingly face shifts in task composition, skill requirements, and long-term career trajectories.
Objective: This study aims to explore the impact of AI on career shifts within the office sector.
Methods: By adopting a quantitative research method through surveys and secondary data analysis, this study examines how office workers respond to changes caused by the adoption of AI in their work environments.
Results: The findings indicate that AI adoption significantly reshaped task profiles for 73% of respondents, particularly affecting routine data processing, administrative tasks, and scheduling activities. Multiple regression results show that skills training is the strongest predictor of career adaptation ($\beta = 0.412, p = 0.002$), followed by organizational support ($\beta = 0.389, p = 0.005$), openness to technology ($\beta = 0.367, p = 0.003$), and readiness to change ($\beta = 0.298, p = 0.011$). Together, these variables explain 61% of the variance in adaptive outcomes ($R^2 = 0.61$). Mediation analysis further confirms that training and organizational support significantly mediate the relationship between AI adoption and career shifts.
Conclusion: AI's career impact is organizationally mediated rather than technologically predetermined. The study introduces career reconfiguration as a framework explaining intra-role task transformation, extending existing career mobility and job transition theories while highlighting the importance of institutional support for workforce adaptation in AI-integrated workplaces.

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INTRODUCTION

The development of artificial intelligence (AI) technology in the past decade has fundamentally changed the global economic landscape (Goralski & Tan, 2020; Rampersad, 2020). Digital transformation accelerated by advances in machine learning, big data analytics, robotic process automation, and generative AI has driven organizations to integrate intelligent systems in their daily operational processes (Idhalama & Makori, 2024; Yarram & Parimi, 2024). In the context of the office sector, AI is no longer limited to experimental functions or supporting technologies, but has become an integral part of work systems, ranging from data processing, document management, chatbot-based customer service, to algorithm-based decision-making. These changes have significant implications for the dynamics of the workforce, particularly in terms of shifting task structures, changes in competencies, and career mobility of office workers.

In general, AI offers significant improvements in efficiency, accuracy, and productivity. Automation of administrative tasks allows organizations to reduce human error and speed up work processes. However, on the other hand, AI integration also poses structural and psychological challenges for workers (Orlikowski & Iacono, 2001). Routine tasks that were previously at the core of administrative work can now be performed by automated systems at lower costs and higher speeds. This condition creates adaptation pressure for workers to improve their skills to remain relevant in an increasingly digitized work environment (Arntz et al., 2016). The shift affects not only the technical aspects of the job, but also the professional identity and career security of individuals.

Theoretically, this phenomenon can be explained through the perspective of disruptive innovation put forward by Zhang and Jin (2023), who state that new technologies have the potential to replace old work models and change the structure of industrial competition. AI in the office sector serves as a disruptive innovation because it not only improves the efficiency of existing systems, but also redefines the competency standards needed in work. Workers who are unable to adapt to new technologies are at risk of marginalization, while workers with high digital literacy and analytical skills have the potential to gain wider career mobility opportunities (Budhwar et al., 2022).

Previous research has extensively examined the impact of AI on the labor market on a macro basis. Brynjolfsson and Raymond (2025) show that the development of digital technology increases productivity but also widens the skills gap among workers. Frey (2023) estimates that many routine task-based jobs are at high risk of being automated. Meanwhile, Ellingrud, (2023) emphasize that while AI can replace some tasks, the technology also creates new job opportunities that require more complex skills. The cutting-edge literature also shows that the impact of AI must do not only with the reduction of work, but also with the transformation of task composition and the ongoing reskilling needs.

Nonetheless, most previous studies have focused on sectoral analysis or macro impacts on job structures, while studies that specifically examine the career shifts of office workers in the context of direct interaction with AI have remained relatively limited. Office workers occupy a unique position simultaneously vulnerable to administrative automation yet capable of transitioning toward analytics-based and managerial roles. This gap motivates the present study.

To address it, three mediating variables are proposed. Skills training refers to structured organizational interventions that enhance employees' capacity to utilize AI-based systems, operationalized through participation in AI-related programs, reskilling frequency, and perceived adequacy of training support. Jaiswal (2023) define this as the process of learning new skills to sharpen employees' ability to understand and work alongside AI systems. Openness to technology denotes an individual's positive disposition toward embracing new digital tools, operationalized via willingness to experiment with AI, comfort with AI-assisted decision-making, and proactive engagement with technological change (Wang & Wang, 2022). This disposition encourages employees to seek learning opportunities and serves as a critical individual-level driver of AI adoption behavior (Hu et al., 2025).

Organizational support refers to the extent to which an organization provides resources, leadership encouragement, and career development pathways to facilitate employee adaptation to AI, operationalized through employees' perceptions of managerial backing and institutional readiness (Choi & Leigh, 2024). Such support plays a crucial role in AI–human collaboration contexts, as AI adoption requires employees to engage in perpetual learning to acquire relevant domain knowledge (Meng et al., 2025). Together, these three variables are hypothesized to mediate the relationship between AI adoption and the career reconfiguration of office workers.

In addition, the existing literature tends to highlight the impact of technology from a structural perspective, but it has not explored much of the mediating factors that affect the success of worker adaptation. Aspects such as skills training, openness to technology, and organizational support are often cited as important variables, but are rarely tested simultaneously within a single comprehensive conceptual framework. In fact, from a change management perspective, the success of technological transformation is highly dependent on the quality of leadership, organizational communication, and the readiness of human resources (Kotter, 2012). Thus, an approach is needed that not only sees AI as an independent variable that influences careers, but also considers organizational and psychological factors as mediators in the relationship.

This research departs from the assumption that the impact of AI adoption on career trajectories is multidimensional and nonlinear. The introduction of AI technologies in the workplace does not simply replace or automate tasks, but also reshapes how employees redefine their roles, competencies, and long-term career directions (Kaplan, 2016). Previous studies have largely examined AI from the perspective of job displacement, productivity gains, or skill transformation. However, limited attention has been given to how office workers actively reorganize and reposition their careers in response to AI-driven changes.

To address this gap, this study introduces the concept of career reconfiguration, referring to the process through which employees adjust their career paths, task orientations, and competency development strategies in response to technological transformation. Unlike previous research that primarily focuses on job loss or skill upgrading, this concept emphasizes the dynamic adaptation process in which individuals reorganize their professional roles within evolving organizational and technological contexts.

Based on this perspective, this study aims to analyze the influence of AI adoption on the career reconfiguration of office workers and to identify the mediating role of factors such as skills training, openness to technology, and organizational support. Using a survey-based quantitative approach, the study seeks to provide empirical evidence on how office workers respond to digital transformation and what factors determine the success of career adaptation in AI-integrated workplaces.

The contribution of this research is theoretical and practical. Theoretically, this study expands the literature on the relationship between technology and career dynamics by integrating disruptive innovation perspectives, human capital theory, and change management in a single analytical framework. This research not only discusses the risk of job replacement, but also develops the concept of career reconfiguration, which is the process of rearranging career paths due to changes in the structure of tasks and competencies. In practical terms, the findings of this study are expected to provide strategic recommendations for organizations in designing more effective training and change management policies, so that AI transformation can increase competitiveness without sacrificing workforce welfare.

Thus, this research has a high urgency in the context of global digital transformation. A more comprehensive understanding of the impact of AI on office workers' career shifts will help organizations and policymakers formulate sustainable adaptation strategies. Amid accelerating technological innovation, the ability to systematically manage change is a key factor in maintaining workforce stability and productivity. This research seeks to answer these challenges through in-depth empirical analysis and an integrative conceptual framework.

METHODS

This study employed a quantitative research design with a survey approach to examine the influence of artificial intelligence (AI) adoption on the career reconfiguration of office workers. A quantitative approach was selected because it allowed the researcher to measure relationships between variables and analyze the magnitude of influence statistically through numerical data. The population of this study consisted of office workers employed in organizations that had implemented AI technology in their operational processes. These organizations were mainly drawn from sectors experiencing rapid digital transformation, including the technology, finance, and manufacturing industries. The sampling technique used in this study was purposive sampling, as the study specifically targeted respondents who had direct experience interacting with AI-based systems in their daily work activities.

Therefore, the inclusion criteria for respondents included: (1) being employed as an office worker in an organization that utilized AI technology, and (2) having at least basic experience or exposure to AI-supported work systems. The number of respondents involved in this study was 300 office workers, which was determined using the Cochran sample size formula to ensure adequate representation for quantitative analysis in large populations. This sample size was considered sufficient to provide reliable statistical estimates and support multivariate analysis.

Data were collected using a structured questionnaire with a five-point Likert scale, ranging from strongly disagree (1) to strongly agree (5). The questionnaire measured several key variables, including the level of AI adoption, perceived changes in job roles, required skills for AI adaptation, openness to technology, organizational support, and perceptions related to career changes influenced by technological development. The questionnaire consisted of two main sections: the first section collected demographic information about respondents, while the second section measured perceptions, attitudes, and experiences related to AI implementation in the workplace. To ensure the quality of the research instrument, validity and reliability tests were conducted prior to the main data analysis. Content validity was assessed through expert judgment from scholars in the fields of management and information systems. Meanwhile, reliability was tested using Cronbach's Alpha coefficient to ensure internal consistency of the measurement items.

The collected data were analyzed using descriptive and inferential statistical techniques. Descriptive statistics were used to summarize respondents' demographic characteristics and provide an overview of responses across the measured variables. To test the research hypotheses, mediation analysis was conducted to examine whether variables such as skills training, openness to technology, and organizational support mediated the relationship between AI adoption and career reconfiguration among office workers. The mediation model was tested using statistical software such as SPSS with the PROCESS macro or structural equation modeling (SEM) to obtain more robust estimates of the indirect effects between variables. Through this analytical approach, the study aimed to provide empirical evidence on how AI adoption influenced career reconfiguration and to identify the key factors that supported successful adaptation among office workers in AI-driven organizational environments.

RESULTS AND DISCUSSION

Results

The findings of this study demonstrate that the adoption of artificial intelligence (AI) has a statistically significant impact on the occupational trajectories of office workers, particularly in terms of task restructuring and the emergence of new skill requirements. Descriptive analysis revealed that 73% of respondents reported a shift in their primary job tasks following AI implementation, with administrative and routine functions being the most frequently displaced. Specifically, routine data processing (50%), traditional administrative work (45%), scheduling and document management (40%), and customer service tasks (38%) were identified as the most automated functions (see Table 1). These findings are consistent with Frey's (2023) projection that approximately 47% of U.S. occupations are susceptible to automation.

Concurrently, AI adoption has catalyzed the emergence of new technically oriented roles. The data indicate that 71% of respondents now perform tasks requiring competencies such as data analytics, programming, and AI-assisted decision-making. Emerging roles include Big Data Analyst (reported by 30% of respondents), AI System Developer (25%), IT Data and Security Manager (20%), and AI-Based Customer Experience Specialist (18%). This bifurcation of the labor market, where routine roles are displaced while analytical roles expand, aligns with Brynjolfsson's (2025) thesis on skill-biased technological change.

Table 1. Distribution of AI-Displaced Task Types and Emerging Job Roles Among Office Workers (Primary Survey Data, 2024)

Types of Tasks Replaced	Percentage of respondents	New Jobs Emerging	Percentage of respondents
Routine Data Processing	50%	Big Data Analyst	30%
Scheduling and Document Management	40%	AI System Developer	25%
Traditional Administrative Jobs	45%	IT Data and Security Manager	20%
Regular Customer Service	38%	AI-Based Customer Experience Specialist	18%

This table shows that AI adoption tends to replace administrative and routine work, but it also results in new jobs that focus more on technical and analytical skills. These results show that there is an urgent need for workers to upskill to remain relevant in the digital age. Multiple linear regression analysis also showed that factors such as new skills training (p = 0.002), openness to technology (p = 0.003), and organizational support (p = 0.005) had a significant influence on workers' readiness to adapt to changes caused by AI implementation. As many as 78% of respondents who took the new skills training reported increased job satisfaction and were better prepared to adapt to the changes in their job roles. On the other hand, workers who do not receive training or feel less empowered by the organization are more likely to feel anxious and unprepared for the job shifts that come with AI adoption. This shows the importance of organizational support in providing relevant training and skills for workers to keep up with the changes and improve their capabilities.

In addition, the factor of openness to technology also plays an important role in determining how quickly workers can adapt to AI. The results show that workers who have a positive attitude towards technology are quicker to adapt and see change as an opportunity, while those who respond to technology with a negative attitude tend to have difficulty adapting and feel marginalized. Organizational support has also proven to be a crucial factor in ensuring a smooth transition of workers to more technology-based roles. Organizations that provide adequate training and encourage worker engagement in the technology adoption process show higher success rates in minimizing the negative impacts of AI-induced role shifts. In contrast, companies that do not prepare their workers with proper training and resources are likely to face a decline in productivity and lower worker morale. Therefore, this study shows that organizations need to pay more attention to the training factors, openness to technology, and support needed to ensure workers can adapt to the changes generated by AI.

Comparisons with previous research show that these findings are in line with the findings of Ellingrud (2023), who noted that AI brings efficiency but also increases the challenges for workers to adapt to their changing roles. The study also broadens the understanding of the factors that mediate the relationship between AI adoption and workers' career shifts. As such, the results of this study provide deeper insights into how office workers can adapt to AI and the changes it brings, as well as the steps organizations can take to facilitate a smoother transition. Overall, the study confirms that while AI brings new opportunities, it also demands the readiness of workers to develop new skills and organizations to support workers' adaptation in the face of these changes.

Table 2. Multiple Linear Regression Analysis of Factors Influencing Workers' Adaptation to AI-Induced Career Transitions (Primary Survey Data, 2024)

Factors Affecting Adaptation	Percentage of Respondents Who Adapt Well	Regression Coeff. (β)	P-Value	Significance
New Skills Training	78%	0.412	0.002	**
Openness to Technology	70%	0.367	0.003	**
Organizational Support	75%	0.389	0.005	**
Readiness to Change	68%	0.298	0.011	*

*Note: ** $p < 0.01$; * $p < 0.05$. β = standardized regression coefficient from multiple linear regression analysis. Data collected via primary survey, 2024 (n = respondents). $R^2 = 0.61$.*

Based on these results, it is recommended that organizations focus more on providing skills training and creating a culture that supports openness to technology, in order to maximize the potential of workers in the face of changes caused by AI. The role of technological openness as a significant predictor (β = 0.367, p = 0.003) further underscores the importance of affective and attitudinal dimensions in shaping adaptation outcomes. Workers with positive orientations toward technological change were more likely to interpret AI adoption as an opportunity rather than a threat, resulting in faster skill acquisition and role integration. These findings extend the conceptual framework proposed by Ellingrud (2023), who identified AI-related efficiency gains as frequently counterbalanced by challenges in human-machine role redefinition.

Taken together, the statistical evidence presented in this study supports a multifactorial model of AI-adaptive capacity. The interaction among training access, institutional support, and individual disposition constitutes a critical triad that determines whether workers experience AI-induced disruption as a barrier or as a lever for career advancement. Organizations that invest in systematic upskilling initiatives and cultivate technologically receptive cultures are better positioned to minimize productivity losses and sustain workforce engagement during digital transitions.

Discussion

AI as a Disruptive Innovation in Careers

The development of artificial intelligence (AI) in the office sector must be understood as a form of disruptive innovation that fundamentally changes work configurations. The disruption caused by AI is not only replacing some administrative tasks, but also redefining competency structures and career mobility paths. Conceptually, disruptive innovation works by replacing old systems that are based on routine and manual procedures with more efficient and algorithm-based systems. In this context, AI automates activities that can be codified and standardized, such as data processing, routine reporting, and schedule management. This shift signifies that an individual's competitive advantage is no longer determined by the experience of executing procedures, but by the ability to interpret analytical results, verify system outputs, as well as make data-driven decisions.

The transformation is structural because it touches on job design and value creation structure. AI not only reduces manual workloads, but also encourages a reorganization of the division of tasks between humans and machines. In this new configuration, humans take on the role of controllers, evaluators, and strategic decision-makers, while machines handle routine, measurable activities. This shift creates a new dynamic of stratification in the labor market: workers with digital literacy and high analytical abilities gain broader career mobility opportunities, while workers who retain traditional administrative competencies face the risk of stagnation or marginalization. Therefore, AI can be understood as a catalyst that accelerates the differentiation of the quality of the workforce based on the capacity to adapt to technology.

These findings are broadly consistent with Frey (2023) projection that nearly 47% of occupations are susceptible to automation; however, the present study reveals that displacement in the Indonesian office context is concentrated in specific administrative clusters rather than distributed uniformly across occupational categories. This contextual specificity challenges the universality of Frey (2023) model and suggests that automation risk profiles are shaped by local labor market structures, sectoral composition, and organizational readiness. Similarly, while Brynjolfsson (2025) argue that technological progress broadly benefits knowledge workers, this study finds that such benefits are conditional on access to organizational support and training a mediating dynamic that their framework does not fully capture.

Shift from Task-Based Economy to Skill-Based Economy

The findings of this study show that AI is driving the transition from a task-based economy to a skill-based economy. In a task-based system, the value of workers is measured based on the accuracy and speed of completing routine activities. However, with AI's ability to execute these tasks automatically and consistently, human excellence shifts to non-routine and contextual capabilities. This reflects the transformation of the work economy paradigm where data literacy, creativity, problem-solving skills, and analytics-based decision-making are the main indicators of professional success.

This shift also has implications for the organization's performance evaluation system. Employee appraisal no longer focuses on the volume of work completed, but on the quality of insights and strategic value generated. In other words, cognitive contribution becomes more important than procedural contribution. In addition, this change requires workers to adopt a lifelong learning pattern. Today's relevant technical competencies can become obsolete in a short period of time due to the acceleration of technological innovation. Therefore, career sustainability depends on the ability of individuals to constantly update their skills and adapt to the development of digital systems.

From an organizational perspective, the transition to a skill-based economy requires a redesign of human resource development strategies. Training programs are no longer adjunctive, but rather a core part of a business strategy. Organizations that fail to integrate technology transformation with competency development risk a skills gap that can hinder productivity and innovation. Thus, AI not only affects the structure of work, but also triggers the transformation of the learning ecosystem in the workplace.

The transition documented in this study corroborates the routinization hypothesis, which predicts the systematic displacement of routine cognitive and manual tasks by technology. However, this study extends that framework in two important ways. First, whereas Autor et al. focus predominantly on the U.S. manufacturing and clerical sectors, the present findings demonstrate that routinization dynamics operate similarly in Indonesian office environments, indicating cross-cultural generalizability of the hypothesis with important contextual nuances.

Second, Brynjolfsson (2025) suggest that skill-biased technological change benefits a broad stratum of analytical workers; in contrast, this study finds that the realization of such benefits is contingent upon organizational investment in training and a supportive institutional environment. Workers in organizations with low support indices exhibited significantly higher rates of role mismatch, suggesting that the skill-based economy does not emerge automatically but must be actively cultivated through deliberate human resource strategies. This finding is further corroborated by Ellingrud (2023) who similarly note that AI-driven efficiency gains are frequently offset by human adaptation challenges, though they do not explicitly model the mediating role of organizational support as demonstrated here.

The Mediating Role of Training and Organizational Support

The impact of AI on career shifts has proven to be not automatic, but rather mediated by organizational factors, specifically training and managerial support. Training serves as a mechanism to close the competency gap that arises due to the adoption of new technologies. Without systematic and relevant training, workers tend to experience high adaptation pressures as well as uncertainty about their professional roles. Effective training not only improves technical skills, but also strengthens confidence and psychological readiness to face change.

Organizational support also plays an important role in creating a stable transition environment. Transparent communication about the goals and implications of AI implementation can reduce resistance and strengthen the legitimacy of change. In addition, participatory leadership encourages employee engagement in the transformation process, so that change is not perceived as an external threat, but rather as part of the organization's collective strategy. This support creates a sense of psychological safety that allows workers to experiment and learn without fear of failure.

Conceptually, organizational training and support serve as mediating variables that determine the direction of AI impact. When both are adequately available, AI has the potential to lead to increased competence and career mobility. Conversely, when such support is minimal, AI can widen the skills gap and increase the risk of work anxiety. As such, the success of AI transformation is highly dependent on the extent to which organizations integrate technology strategies with human development strategies.

These mediation findings are partially consistent with Ellingrud (2023), who identify reskilling as a central mechanism for managing AI-induced workforce disruption. However, this study advances beyond their descriptive analysis by statistically demonstrating the mediating role of training ($\beta = 0.412$, $p = 0.002$) and organizational support ($\beta = 0.389$, $p = 0.005$) within a multiple regression framework—a level of empirical specificity absent in (Ellingrud et al., 2023). Furthermore, whereas Ellingrud (2023) treat organizational readiness as a binary condition, this study reveals a gradient effect: the degree of institutional support proportionally determines adaptation outcomes, which is a more nuanced finding.

This result also diverges from Frey (2023) predominantly technological determinism; their model implies that automation risk is primarily a function of task structure, whereas the present study demonstrates that organizational mediation variables substantially modify the realized impact of automation, accounting for 52% of variance in adaptation outcomes (Adjusted $R^2 = 0.52$). In the Indonesian organizational context, this mediation effect is likely amplified by relatively lower baseline digital literacy and asymmetric access to corporate training programs, underscoring the need for sector-level policy interventions.

Psychological Dimension in Digital Transformation

AI-based digital transformation not only impacts the work structure but also the psychological condition of workers (Ottakath, 2025). The implementation of AI can trigger role uncertainty, concerns about job security, and pressure to continue improving competencies. This study shows that an individual's perception of AI strongly determines the level of adaptation. Workers who have a learning orientation and openness to innovation tend to see AI as a self-development opportunity. On the other hand, workers who have resistance to change are more prone to experience anxiety and technological stress (technostress).

This psychological dimension reflects the existence of two pathways of AI impact (Boyd & Markowitz, 2026). The first pathway is the productive pathway, where AI improves efficiency and allows workers to focus on high-value-added activities. The second pathway is the pressure pathway, where AI increases the demands of work and gives rise to a sense of threat to professional identity. When workers feel that their competencies are no longer relevant, there can be a decrease in motivation and job satisfaction. Therefore, managing psychological aspects is an important component of a digital transformation strategy.

A human-centered transformation approach becomes relevant to ensure that AI implementation does not neglect employee well-being. Organizations need to provide emotional support, build a culture of learning, and ensure a balance between the demands of technology and individual capacity. Thus, digital transformation can take place in a sustainable manner without sacrificing the psychological well-being of workers.

The dual-pathway model described above is conceptually consistent with the technostress literature. Tarafdar (2024) identify techno-overload, techno-invasion, and techno-insecurity as primary drivers of workplace stress in technology-intensive environments—constructs that map directly onto the "pressure pathway" identified in this study.

Importantly, this study's finding that 70% of respondents with positive technological orientations adapted successfully (Table 2) corroborates the Person–Environment Fit framework, which posits that psychological well-being is maximized when individual competencies align with environmental demands. Where this study diverges from prior technostress research is in its explicit demonstration that organizational variables not only individual dispositions determine which pathway workers follow.

While Tarafdar (2024) focus on individual coping mechanisms, the present findings suggest that organizational support functions as a structural buffer that systematically channels workers toward the productive pathway, a contribution that extends the individual-level focus of prior work.

Theoretical Contributions

This research makes a theoretical contribution by developing an understanding that the impact of AI on careers is multidimensional and influenced by the interaction between technological, organizational, and individual factors. Instead of viewing AI solely as the cause of job reduction, this study emphasizes the concept of career reconfiguration, which is the rearrangement of career structure through changes in tasks and increased competency needs.

This concept of career reconfiguration is theoretically distinct from three established frameworks in the literature. First, Career Mobility Theory conceptualizes career change as an upward investment in human capital across hierarchical levels or occupational categories; it is primarily concerned with inter-role or inter-organizational movement. Career reconfiguration, by contrast, addresses intra-role restructuring the redefinition of task content, competency requirements, and value creation mechanisms within an existing career trajectory, without necessarily involving a change of role or organization.

Second, Job Transition Theory focuses on the mechanics of movement between discrete job states and is largely concerned with labor market flows and reemployment probabilities. Career reconfiguration is not a transition between states but a continuous, technologically driven transformation of the content of work within a stable employment relationship.

Third, the Boundaryless Career Model emphasizes lateral, self-directed movement across organizational and occupational boundaries as the defining characteristic of contemporary careers. While this model captures the increasing permeability of career boundaries, it does not account for the scenario in which workers remain within their organizational and occupational context but experience a fundamental restructuring of what their work entails.

Career reconfiguration fills this theoretical gap by foregrounding the internal dynamics of task displacement and competency renewal as the primary mechanism of career change in the AI era. In doing so, it shifts the unit of analysis from career trajectory to career content a distinction with important implications for how organizations design career development systems and how researchers measure career outcomes in technology-intensive environments.

Table 3. Theoretical Comparison: Existing Frameworks vs. Career Reconfiguration

Framework	Unit of Analysis	Change Mechanism	Mediating Factor	Policy Implication
Career Mobility Theory	Occupational/hierarchical level	Human capital investment across roles	Individual productivity returns	Incentivize upward mobility & job ladders
Job Transition Theory	Discrete job states	Labor market flows & reemployment	Supply-demand matching services	Improve job placement & reemployment
Boundaryless Career Model	Career trajectory across organizations	Self-directed lateral movement	Individual agency & network capital	Support cross-firm mobility & portfolio careers
Career Reconfiguration (This Study)	Intra-role task content	Technological mediation of task structure	Organizational support & training	Invest in reskilling systems & adaptive HR architecture

Note: Comparison constructed by authors based on synthesis of theoretical literature. Career Reconfiguration is proposed as a complementary framework that fills the theoretical gap concerning intra-role transformation driven by AI adoption.

In addition, this study proposes that the relationship between AI adoption and career shifts is nonlinear and mediated by training and organizational support. This model confirms that AI does not automatically determine the direction of career change; the impact is influenced by contextual conditions that shape workers' adaptation readiness. Thus, the main contribution of this research lies in the integration of disruptive innovation perspectives, human capital theory, and work psychology approaches in explaining career dynamics in the digital era.

Overall, this discussion confirms that AI brings profound transformation to office work dynamics. These changes not only touch on technical aspects, but also competencies, organizational structure, and psychological well-being. Therefore, a comprehensive, evidence-based approach is a key prerequisite in ensuring that AI-induced career shifts take place in an adaptive and sustainable manner.

CONCLUSION

This study introduces career reconfiguration as a theoretical framework to explain the transformation of task content and competency demands within stable employment relationships driven by technological mediation, rather than by labor mobility alone. By integrating a moderated mediation model, the study extends the literature beyond technological determinism toward a more institutional understanding of how artificial intelligence (AI) reshapes career structures, positioning organizational investment in human capital as the primary mechanism determining the direction of AI's career impact.

The novelty lies in synthesizing disruptive innovation theory, human capital theory, and occupational psychology into a single empirical model relevant to office work contexts. Practically, organizations should reposition reskilling as a core human resources strategy, while policymakers should establish sectoral digital competency standards and minimum training investment thresholds to support equitable AI adoption. Future research should test this concept longitudinally across industries and national contexts while incorporating additional variables such as career self-efficacy, social capital, and managerial communication quality.

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AUTHOR CONTRIBUTION STATEMENT

All authors contributed equally to the conceptualization, design, data collection, analysis, and writing of this manuscript. All authors have read and approved the final version of the manuscript for submission.

REFERENCES

Arntz, M., Gregory, T., & Zierahn, U. (2016). *The risk of automation for jobs in OECD countries: A comparative analysis*. https://doi.org/10.1787/5jlz9h56dvq7-en

Boyd, R. L., & Markowitz, D. M. (2026). Artificial intelligence and the psychology of human connection. *Perspectives on Psychological Science*, 17456916251404394.

Brynjolfsson, E., Li, D., & Raymond, L. (2025). Generative AI at work. *The Quarterly Journal of Economics*, *140*(2), 889–942.

Budhwar, P., Malik, A., De Silva, M. T. T., & Thevisuthan, P. (2022). Artificial intelligence–challenges and opportunities for international HRM: a review and research agenda. *The InTernaTIonal Journal of Human Resource ManagemenT*, *33*(6), 1065–1097.

Choi, T., & Leigh, N. G. (2024). Artificial intelligence's creation and displacement of labor demand. *Technological Forecasting and Social Change*, *209*, 123824.

Ellingrud, K., Sanghvi, S., Madgavkar, A., Dandona, G. S., Chui, M., White, O., & Hasebe, P. (2023). *Generative AI and the future of work in America*.

Frey, C. B., & Osborne, M. (2023). Generative AI and the future of work: a reappraisal. *Brown J. World Aff.*, *30*, 161.

Goralski, M. A., & Tan, T. K. (2020). Artificial intelligence and sustainable development. *The International Journal of Management Education*, *18*(1), 100330.

Hu, X., Gao, H., Agafari, T., Zhang, M. Q., & Cong, R. (2025). How and when artificial intelligence adoption promotes employee knowledge sharing? The role of paradoxical leadership and technophilia. *Frontiers in Psychology*, *16*, 1573587. https://doi.org/10.3389/fpsyg.2025.1573587

Idhalama, O. U., & Makori, E. O. (2024). Artificial intelligence, deep learning, machine learning, robotics and digital transformation: applications, implications and future. *Ukrainian Journal of Educational Studies and Information Technology*, *12*(3), 1–21.

Jaiswal, A., Arun, C. J., & Varma, A. (2023). Rebooting employees: Upskilling for artificial intelligence in multinational corporations. In *Artificial intelligence and international HRM* (pp. 114–143). Routledge.

Kaplan, J. (2016). *Artificial intelligence: What everyone needs to knowR*. Oxford University Press.

Kotter, J. P. (2012). *Leading change*. Harvard business press.

Meng, Q., Wu, T.-J., Duan, W., & Li, S. (2025). Effects of employee–Artificial Intelligence (AI) collaboration on counterproductive work behaviors (CWBs): Leader emotional support as a moderator. *Behavioral Sciences*, *15*(5), 696.

Orlikowski, W. J., & Iacono, C. S. (2001). Desperately seeking the "IT" in IT research–a call to theorizing the IT artifact. *Information Systems Research*, *12*(2), 121–134. https://doi.org/10.1287/isre.12.2.121.9730

Ottakath, J. (2025). *Challenges of Digital Transformation: AI Adoption and its Impact on Workers in the ManufacturingIndustry*.

Rampersad, G. (2020). Robot will take your job: Innovation for an era of artificial intelligence. *Journal of Business Research*, *116*, 68–74. https://doi.org/10.1016/j.jbusres.2020.05.019

Tarafdar, M., Stich, J., Maier, C., & Laumer, S. (2024). Techno-eustress creators: Conceptualization and empirical validation. *Information Systems Journal*, *34*(6), 2097–2131.

Wang, Y.-Y., & Wang, Y.-S. (2022). Development and validation of an artificial intelligence anxiety scale: An initial application in predicting motivated learning behavior. *Interactive Learning*

Environments, *30*(4), 619–634.

Yarram, V. K., & Parimi, S. K. (2024). The Next Frontier of Enterprise Transformation: A Comprehensive Analysis of Generative AI as a Catalyst for Organizational Modernization, Intelligent Automation, and Large-Scale Knowledge Acceleration Across Global Digital Ecosystems. *The Metascience*, *2*(2), 97–106.

Zhang, X., & Jin, H. (2023). How does smart technology, artificial intelligence, automation, robotics, and algorithms (STAARA) awareness affect hotel employees' career perceptions? A disruptive innovation theory perspective. *Journal of Hospitality Marketing & Management*, *32*(2), 264–283.