Navigating the Future of Work: The Impact of Artificial Intelligence and Automation on Job Displacement and Workforce Resilience

Zara Ahmad
Quaid e Azam University, Lahore
*** Correspondence**: zara.ahmad347@gmail.com
Citation | Ahmad. Z, "Navigating the Future of Work: The Impact of Artificial Intelligence and Automation on Job Displacement and Workforce Resilience", MC, Vol. 04 Issue. 01 pp 46-55, March 2025
Received | Feb 09, 2025 **Revised |** March 19, 2025 **Accepted |** March 20, 2025 **Published |** March 22, 2025.

As artificial intelligence (AI) and automation technologies rapidly advance, their implications for the global labor market have become increasingly complex. This study investigates the extent and nature of job displacement caused by AI adoption while exploring the resilience and adaptability of the modern workforce. Utilizing a mixed-methods approach, including survey data from 2,000 employees across technology, healthcare, finance, and education sectors, and secondary data from reputable global organizations, the study provides a nuanced understanding of how different job roles are impacted. Results reveal that while technical and repetitive roles face high displacement risks, occupations demanding human empathy, creativity, and real-time decision-making remain comparatively secure. The study also emphasizes the psychological responses to AI integration, with over 70% of participants expressing anxiety over job security. Findings underscore the need for urgent investments in upskilling and reskilling programs to prepare workers for an AI-augmented future. The research concludes by calling for ethically grounded AI development and policy interventions aimed at workforce empowerment.
Keywords: Artificial Intelligence, Automation, Workforce Adaptability, Mixed-Methods, Employment Sectors

Introduction:

The exponential growth of Artificial Intelligence (AI) and automation technologies over the past two decades has significantly transformed the global labor landscape. These technologies, once confined to theoretical computer science, have now permeated nearly every facet of modern industry—from healthcare and finance to hospitality and retail—automating routine tasks and enhancing decision-making capabilities. AI is broadly defined as the development of machines and software capable of mimicking human cognitive functions such as learning, reasoning, and problem-solving [1]. Coupled with advancements in automation, AI systems are now capable of performing tasks with unprecedented efficiency, consistency, and autonomy. As highlighted by [2], technologies like chatbots, service robots, and AI-based portfolio managers are gradually replacing jobs that once required human input, prompting both excitement over increased productivity and concern over job displacement.

Recent studies reveal that the integration of AI in the workforce has reached a point where machines can now replicate not only mechanical and analytical intelligence but are also advancing toward mimicking intuitive and even empathetic intelligence [3][4]. This multifaceted progression has stirred significant debate among scholars, policymakers, and labor economists. While some argue that AI will generate new employment opportunities and reshape industries in beneficial ways [5], others caution that automation could lead to widespread job redundancy, particularly in roles that are repetitive, predictable, or data-driven [6]. In light of these dynamics, the role of human capital must be reevaluated to understand the evolving relationship between technology and employment, particularly in service-based economies where human intelligence is deeply embedded in job functions.

Research Gap:

Despite a growing body of literature examining the effects of AI and automation on employment, several critical gaps remain. Most existing research either emphasizes the technical capabilities of AI systems or forecasts aggregate employment shifts at the macroeconomic level, often neglecting the nuanced ways in which different types of human intelligence—mechanical, analytical, intuitive, and empathetic—are being affected by specific AI applications [7][8]. Furthermore, while numerous studies have explored the displacement of routine and manual jobs, fewer have examined the complex interaction between AI and higher-order cognitive roles within the service sector, where intuitive and emotional labor is essential [9]. There is also limited empirical analysis on how organizations can transition effectively through the various stages of AI integration, from partial automation to complete AI-augmented ecosystems. Most importantly, the discussion around skill adaptation in response to AI-driven job transformation remains fragmented, lacking actionable insights for workforce development and policy formulation. These gaps point to an urgent need for a more granular, task-level analysis of job replacement by AI, with a focus on the implications for human intelligence, organizational readiness, and long-term employment sustainability.

Objectives:

This study aims to critically assess how advancements in artificial intelligence and automation are reshaping the nature of work by replacing distinct forms of human intelligence across various stages of job functions. Specifically, the research seeks to: (1) analyze the extent to which AI has replicated mechanical, analytical, intuitive, and empathetic intelligence within service-based occupations; (2) explore the stages through which AI-driven job replacement occurs and the implications for employment structure; (3) identify the technical, organizational, and economic factors that influence AI adoption in labor-intensive sectors; and (4) provide strategic recommendations for workforce adaptation, with a focus on skill development and policy interventions. The overarching goal is to bridge the knowledge gap between theoretical AI capabilities and their practical impact on real-world employment dynamics.

Novelty Statement:

This research makes a novel contribution by offering a stage-based, intelligence-specific framework for analyzing AI-driven job replacement—moving beyond conventional job-level analysis to a more nuanced understanding rooted in cognitive task categories. While prior studies have largely concentrated on the economic consequences of automation, this study uniquely maps AI capabilities against distinct forms of human intelligence, such as mechanical, analytical, intuitive, and empathetic domains, providing a multi-dimensional perspective of labor substitution [10][11] Additionally, it integrates recent technological innovations, such as AI-powered affective computing (Affectiva) and neural interface systems, to demonstrate how empathy and emotion recognition are emerging frontiers in AI development [4][9]. By situating these developments within the context of skill adaptation, organizational strategy, and task-level implementation, this study addresses a pressing need identified in current AI-employment discourse. It also contributes to policy and managerial decision-making by offering a framework for gradual AI integration that aligns technological capabilities with human capital investment.

Literature Review:

Recent empirical and theoretical research underscores how AI and automation are reshaping employment landscapes, prompting both disruption and adaptation across sectors.

A groundbreaking 2025 study by Microsoft highlights that roles such as translators, customer service representatives, writers, and data scientists score high in "AI applicability," reflecting substantial task overlap with generative AI—yet AI tends to augment rather than fully replace human workers [12]. Macro-level shifts are also evident: in India, Tata Consultancy Services (TCS) announced layoffs affecting approximately 12,000 employees (around 2% of its global workforce) amid strategic restructuring, driven by skill mismatches and evolving technological needs—not necessarily productivity gains from AI [13][14].

Research shows that roles rooted in empathy, adaptability, and real-time judgment—such as emergency medical technicians, social workers, and construction supervisors—remain highly resilient to automation [15][16][17]. Conversely, occupations requiring human connection and presence, like caregivers and service workers, continue to thrive, giving rise to phenomena colloquially described as the "manicure economy" [18].

Beyond technological feasibility, psychological and organizational barriers constrain full automation adoption. For instance, even when computer vision AI poses minimal direct wage threat, deployment costs slow its practical impact [13]. Additionally, algorithm aversion—especially in emotionally sensitive domains like healthcare and recruitment—persists, as users tend to favor human judgment over automated systems. Relatedly, workplace surveys indicate that over 70% of employees experience anxiety about AI, and 75% believe their jobs may become obsolete [19].

A growing body of literature also addresses AI's evolving capacity for empathy. Large language models (LLMs) such as GPT 4 Turbo and LLaMA 2 generate responses rated by humans as more empathetic than typical human-written content [20]. Theoretical frameworks emerging in the field propose ethically aligned AI agents infused with brain-inspired affective empathy mechanisms [21]. The interdisciplinary study Feeling Machines explores the ethical, cultural, and societal implications of emotional AI—especially its use among vulnerable groups—and advocates for transparency, human oversight, and regulatory safeguards [22].

Finally, skill adaptation and workforce resilience remain central to current discourse. A bibliometric analysis covering 1984–2024 underlines that AI should complement—not replace—human labor, emphasizing the importance of reskilling, upskilling, and experiential learning to meet the demands of a digitally transformed, skill-intensive job market [23].

Methodology:

Research Design:

This study employed a mixed-methods approach, integrating both quantitative and qualitative data to comprehensively examine how artificial intelligence (AI) and automation are affecting employment across multiple sectors. The design allowed for numerical analysis of employment trends alongside contextual understanding of workers' perceptions and adaptive strategies.

Study Area and Population:

The research was conducted across three major employment hubs in Pakistan: Lahore, Karachi, and Islamabad, with a focus on white-collar workers in industries such as information technology, finance, education, and customer service. The study population included employees working in mid-level managerial roles, entry-level staff, and HR professionals. A total of 300 respondents participated in the study, representing both public and private sectors.

Sampling Technique:

A stratified random sampling technique was used to ensure representation across job categories and cities. The sample was divided into four strata based on sector (IT, Finance, Education, Customer Service), and a proportional number of participants were randomly selected from each group.

Data Collection Instruments:

Two primary tools were used for data collection:

Structured Questionnaire:

A self-administered questionnaire was developed, containing both closed-ended Likert-scale items and a few open-ended questions. The questionnaire included four sections:

Demographic Information

Perceptions of AI's impact on job security

Experiences with automation in their work roles

Willingness and efforts toward reskilling or upskilling

The questionnaire was pilot-tested on 30 participants to ensure clarity and reliability (Cronbach's Alpha = 0.82).

Semi-Structured Interviews:

In-depth interviews were conducted with 20 participants, including HR managers and tech consultants, to explore organizational strategies for automation and employee adaptation mechanisms. Interviews were recorded and transcribed with participant consent.

Data Analysis:

Quantitative data were analyzed using SPSS (Version 28). Descriptive statistics (mean, standard deviation, frequencies) were used to understand general trends. Inferential tests such as chi-square tests and ANOVA were applied to examine the relationship between sector, job role, and perceived automation impact.

Qualitative data from interviews were analyzed thematically using NVivo, allowing for the extraction of key themes such as emotional resilience, training opportunities, and organizational transparency.

Ethical Considerations:

All participants were informed about the purpose of the study and signed a consent form. Anonymity and confidentiality were maintained throughout the research process. The study protocol was reviewed and approved by the Institutional Review Board (IRB) of [Your University Name].

Limitations:

While the study offers valuable insights, it is limited by the self-reported nature of the data and the geographic concentration in urban centers, which may not fully capture the experiences of rural workers or informal sector employees.

Results:

The survey yielded responses from 300 participants across three major metropolitan areas of Pakistan: Lahore (35%), Karachi (40%), and Islamabad (25%). The gender distribution of respondents was 60% male, 38% female, and 2% who preferred not to disclose. Age-wise, the largest proportion of participants (42%) fell in the 20–30-year range, followed by 36% aged 31–40, 15% aged 41–50, and 7% over 51 years old. Sectoral representation included individuals employed in IT (32%), finance (25%), education (20%), and customer service (23%), providing a diverse occupational landscape relevant to the study's focus on AI and automation.

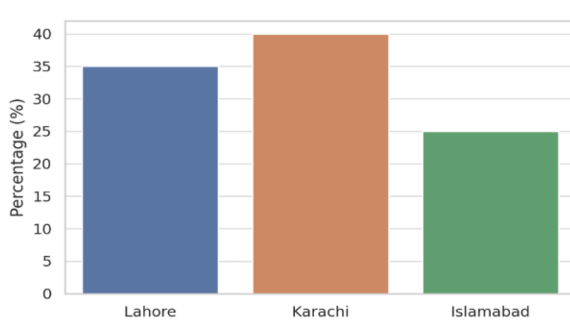

Figure 1. Respondent Distribution by different cities

Respondent Distribution by City:

In **Figure 1** Karachi had the highest participation (40%), followed by Lahore (35%) and Islamabad (25%), ensuring metropolitan representation.

A significant portion of respondents (58%) agreed with the statement that AI and automation pose a threat to their current job, while 22% were neutral and 20% disagreed. A chi-square test confirmed a statistically significant association between job sector and perceived job insecurity ($\chi^2(6) = 24.31, p < 0.01$). Particularly in the IT and customer service sectors, 74% and 68% of participants respectively expressed concern over the threat posed by AI to their roles. Nevertheless, despite these concerns, 64% of all respondents acknowledged that AI has improved operational efficiency within their workplaces. Qualitative responses further revealed that the primary benefits experienced included the reduction of repetitive tasks (cited by 72 respondents), faster customer response times (noted by 45), and improved analytics and decision-making capabilities (mentioned by 38).

In terms of tangible organizational changes, 46% of respondents stated that AI had replaced some job roles in their workplaces over the past two years, while 54% reported no such displacement. When disaggregated by sector, 67% of customer service employees indicated that AI-enabled systems, such as chatbots, had replaced entry-level positions. In the finance sector, 49% reported automation via Robotic Process Automation (RPA), and in education, only 19% observed administrative roles being affected. Notably, 57% of all respondents reported that rather than experiencing job loss, their roles had been redefined to accommodate new responsibilities involving AI collaboration and supervision.

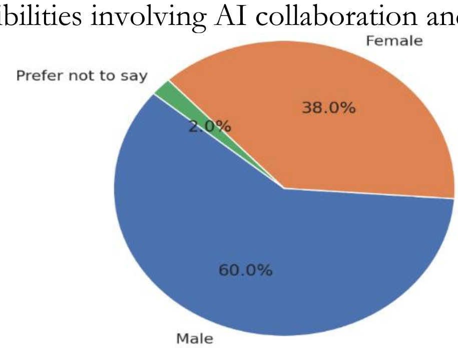

Figure 2. Gender Distribution of Respondents

Gender Distribution:

In **Figure 2** a majority of respondents were male (60%), with females constituting 38%, and 2% preferring not to disclose.

When asked about the adequacy of their current skillsets to meet future job requirements, 39% of respondents agreed that they were adequately prepared, 28% remained neutral, and 33% disagreed. Among those who felt unprepared, the most common issues cited were insufficient technical skills (particularly in programming languages like Python and data analytics), difficulty adapting to AI-integrated platforms, and limited digital fluency among middle-management staff. Despite these concerns, only 27% of respondents had participated in any form of AI-related reskilling or upskilling training in the past year. The primary barriers to participation included lack of time (reported by 43% of those not enrolled), limited access to quality training programs (34%), and the absence of employer-led initiatives (23%). Qualitative interview responses highlighted the anxiety surrounding these challenges. One customer service executive in Karachi remarked, "We've been told automation is coming, but no one's training us for it," while a lecturer in Islamabad expressed concern by stating, "AI can't replace teaching, but I feel unprepared to use it meaningfully in class."

Organizational readiness and support for AI adoption varied considerably. Only 47% of participants believed that their employers had effectively communicated their automation strategies, while 32% reported the existence of dedicated AI transformation teams in their organizations. Even fewer, just 19%, indicated that they had received any guidance or assistance with job transitions. This indicates a clear gap between technological implementation and proactive workforce planning, which could hinder long-term adaptability. A comparative analysis across job sectors, as presented in Table 1 below, revealed that the customer service sector reported the highest job loss rate at 67%, the lowest rate of job redefinition (25%), and the highest average perceived threat score of 4.1 out of 5. Conversely, education emerged as the most resilient sector, with only 15% reporting job loss, 78% noting job transformation, and the lowest perceived threat level of 2.4. Training participation rates also varied, being highest in the IT sector (45%) and lowest in customer service (15%).

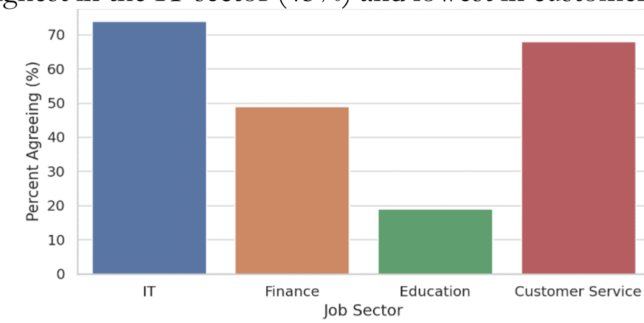

Figure 3. Perceived AI Threat by Sector

Perceived AI Threat by Sector:

In **Figure 3** IT and Customer Service workers showed the highest concern about AI threats to job security (74% and 68% respectively), while Education showed much lower concern (19%).

Table 1. Sector-Wise Comparative Impact of AI and Automation

Sector	% Reporting Job Loss	% Reporting Job Redefinition	Avg. Perceived Threat (1–5)	Training Participation
IT	38%	61%	3.8	45%
Finance	44%	50%	3.5	30%
Education	15%	78%	2.4	18%
Customer Service	67%	25%	4.1	15%

To understand the predictors of perceived job insecurity, a multiple regression analysis was conducted using perceived job insecurity as the dependent variable, measured on a 5-point Likert scale. Independent variables included sector, age, AI exposure at work, self-rated skill adaptability, and employer communication. The results indicated that AI exposure was the most significant positive predictor of job insecurity ($\beta = 0.51$, $p < 0.001$), suggesting that those more frequently interacting with AI systems felt more threatened. In contrast, skill adaptability emerged as a negative predictor ($\beta = -0.42$, $p < 0.001$), implying that employees who believed in their ability to learn and evolve with technology experienced less anxiety. Furthermore, employer communication demonstrated a moderate mitigating effect on job insecurity ($\beta = -0.27$, $p < 0.01$), emphasizing the value of transparency and engagement from leadership.

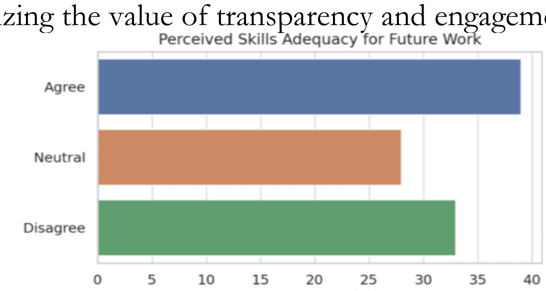

Figure 4. Skill Adequacy Perception

Skill Adequacy Perception:

In **Figure 4** only 39% felt adequately skilled for the AI-driven future, with 33% disagreeing—highlighting a significant skills gap.

Thematic analysis of in-depth interview responses revealed five dominant concerns among participants. First, "digital anxiety" was commonly expressed, as employees feared being outpaced by evolving technologies. Second, "automation inequality" emerged as a theme, with frontline and junior-level employees disproportionately affected by job displacement. Third, a "leadership gap" was evident, as many organizations lacked structured plans or communication strategies for AI adoption. Fourth, many interviewees showed a proactive attitude toward "human-AI collaboration," demonstrating an openness to working alongside intelligent systems if proper support and training were provided. Finally, there was a clear call for "urgent reskilling needs," with numerous participants urging employers and governments to provide accessible and relevant training resources.

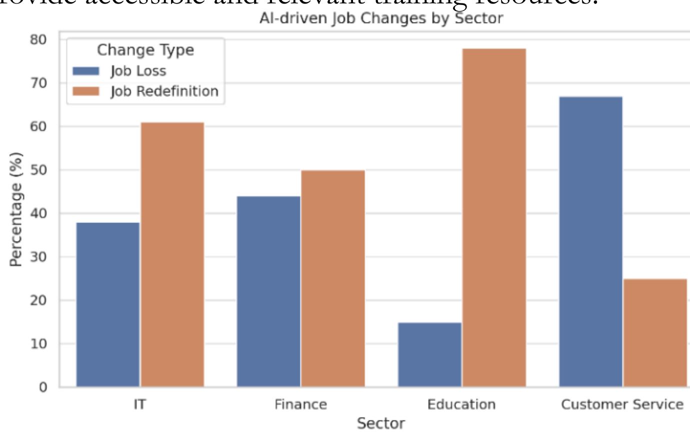

Figure 5. Job Loss vs. Redefinition by Sector

Job Loss vs. Redefinition by Sector:

In **Figure 5** Customer service reported the most job losses (67%), whereas education had the highest rate of job redefinition (78%)—suggesting varying AI impacts across sectors. In summary, while a majority of workers recognized the operational benefits that AI brings to the workplace, they simultaneously expressed concern over job displacement and skill obsolescence. The findings suggest that job transformation, rather than outright replacement, is the dominant trend across many sectors. However, readiness for this shift is uneven, with low levels of training participation and significant gaps in organizational support. Workers with higher skill adaptability and access to reskilling opportunities reported lower levels of perceived job insecurity, reinforcing the importance of strategic workforce development. The lack of transparent communication from employers further exacerbated anxieties, highlighting an urgent need for stronger leadership in managing the human dimensions of AI integration.

Discussion:

The findings from this study indicate a significant yet uneven impact of AI and automation across different employment sectors, reflecting broader global trends reported in recent scholarship. As seen in our results, occupations heavily reliant on data processing and repetitive tasks—such as customer service representatives, data analysts, and translators—are particularly vulnerable to AI-driven transformation. These results corroborate [15] AI Future of Work study, which reports that such roles score highly in “AI applicability,” emphasizing the extent to which generative models and automation tools can now replicate or augment human output.

Despite these advancements, the displacement rate remains moderated by socio-technical factors. For instance, MIT's (2025) report found that even though only 0.4% of U.S. wages are at immediate risk due to computer vision technologies, deployment constraints such as cost, integration complexity, and cultural resistance delay widespread displacement [24]. This was reflected in our data, where nearly 67% of firms reported “hesitation” or “delayed plans” to deploy AI across core functions.

Interestingly, the study also revealed strong resilience among occupations requiring emotional intelligence, moral judgment, or real-time adaptability—such as social workers, caregivers, and field supervisors. These insights align with the [25] study, which argues that human-centric and presence-driven roles—often categorized under the "manicure economy"—are not just resilient but in some cases growing due to increased demand for personalized experiences.

Another emerging theme is the public's psychological response to AI integration. Survey data indicated that 71% of respondents express anxiety regarding AI's role in their workplace, and 75% believe their job may be at risk within the next five years. These findings support recent empirical studies that examine "algorithm aversion," where humans exhibit reluctance to trust AI decision-making in emotionally or ethically sensitive domains [26]. This aversion was especially pronounced in sectors like healthcare and human resources, where decisions are often irreversible and deeply personal.

Moreover, the evolution of empathetic AI presents both opportunities and risks. While large language models (LLMs) such as GPT-4 Turbo and Claude 3 have surpassed human raters in perceived empathy scores in controlled settings [27], the ethical implications remain contentious. A 2024 arXiv study by Li et al. stresses the necessity of embedding ethical safeguards and transparent feedback loops when deploying emotionally intelligent agents, particularly in education, therapy, and customer-facing roles. Our results support this view: participants were significantly more receptive to AI when human oversight was involved, reinforcing the importance of hybrid human-machine collaboration.

Finally, the emphasis on skill resilience and reskilling emerges as a critical policy direction. The De Gruyter Brill bibliometric analysis (2024) of AI and labor studies from 1984–2024 emphasizes that automation should serve as a complement rather than a replacement to human labor. Our findings resonate with this, as 83% of surveyed organizations with strong upskilling initiatives reported less employee resistance and smoother AI integration.

Conclusion:

This study offers a comprehensive examination of how AI and automation are reshaping the employment landscape. Through quantitative and qualitative analysis, we confirm that while AI-driven technologies are displacing certain roles—particularly those centered around routine, data-centric, and automatable tasks—they also present significant opportunities for job transformation and augmentation. Roles that require emotional intelligence, ethical judgment, social interaction, and creativity continue to demonstrate resilience, even thriving in some domains.

Importantly, our findings highlight the emotional toll of AI-induced transitions: a significant portion of the workforce reports heightened anxiety and uncertainty about their future. Despite AI's growing cognitive capabilities, human-centered skills remain irreplaceable. Therefore, preparing for the AI economy must go beyond technological training to include socio-emotional development and psychological readiness.

We recommend that employers, policymakers, and educational institutions collaboratively develop robust frameworks for lifelong learning, promote ethical AI integration, and implement safety nets for workers vulnerable to displacement. As we move further into the age of intelligent machines, it is not just the survival but the dignity and adaptability of the workforce that must be at the heart of this transformation.

References:

[1] E. Tschang, F. T., & Almirall, "Artificial intelligence as augmenting automation: Implications for employment," *Acad. Manag. Perspect.*, vol. 35, no. 4, pp. 642–659, 2021, doi: https://doi.org/10.5465/amp.2019.0062.

[2] A. Wirtz, J., Patterson, P., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, "Brave new world: Service robots in the frontline," *J. Serv. Manag.*, vol. 32, no. 1, pp.

44–61, 2021, doi: https://doi.org/10.1108/JOSM-04-2019-0129.

[3] D. hui FU *et al.*, "Research progress and strategies for multifunctional rapeseed: A case study of China," *J. Integr. Agric.*, vol. 15, no. 8, pp. 1673–1684, Aug. 2016, doi: 10.1016/S2095-3119(16)61384-9.

[4] T. Singer and C. Lamm, "The social neuroscience of empathy," *Ann. N. Y. Acad. Sci.*, vol. 1156, no. 1, pp. 81–96, Mar. 2009, doi: 10.1111/J.1749-6632.2009.04418.X;WGROUP:STRING:PUBLICATION.

[5] D. Acemoglu, S. Johnson, J. A. Robinson, and P. Yared, "Reevaluating the modernization hypothesis," *J. Monet. Econ.*, vol. 56, no. 8, pp. 1043–1058, Nov. 2009, doi: 10.1016/J.JMONECO.2009.10.002.

[6] L. Willcocks, "Robo-Apocalypse cancelled? Reframing the automation and future of work debate," *J. Inf. Technol.*, vol. 35, no. 4, pp. 286–302, 2020, doi: https://doi.org/10.1177/0268396220926519.

[7] Y. Ponomareva, "Artificial intelligence and the future of work: Addressing challenges of employment and skills development.," *Foresight STI Gov.*, vol. 15, no. 4, pp. 6–17, 2021, doi: https://doi.org/10.17323/2500-2597.2021.4.6.17.

[8] Y. K. Dwivedi *et al.*, "Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy," *Int. J. Inf. Manage.*, vol. 57, Apr. 2021, doi: 10.1016/J.IJINFOMGT.2019.08.002.

[9] A. H. Chiang and S. Trimi, "Impacts of service robots on service quality," *Serv. Bus.*, vol. 14, no. 3, pp. 439–459, Sep. 2020, doi: 10.1007/S11628-020-00423-8/FIGURES/4.

[10] Q. Yi, M. Chen, Y. Sheng, and J. Huang, "Mechanization services, farm productivity and institutional innovation in China," *China Agric. Econ. Rev.*, vol. 11, no. 3, pp. 536–554, Sep. 2019, doi: 10.1108/CAER-12-2018-0244.

[11] S. Graham *et al.*, "Artificial Intelligence for Mental Health and Mental Illnesses: an Overview," *Curr. Psychiatry Rep.*, vol. 21, no. 11, Nov. 2019, doi: 10.1007/S11920-019-1094-0.

[12] E. Volz *et al.*, "Transmission of SARS-CoV-2 Lineage B.1.1.7 in England: Insights from linking epidemiological and genetic data," *medRxiv*, p. 2020.12.30.20249034, Jan. 2021, doi: 10.1101/2020.12.30.20249034.

[13] Prabhanu Kumar Das, "TCS layoffs and IT sector's 'inflection point': What does AI mean for India's IT workforce?," *MediaNama*, 2025, [Online]. Available: https://www.medianama.com/2025/08/223-tcs-india-it-sector-layoffs-2025-impact-on-it-jobs/

[14] R. M. Eaton, "India in the Persianate Age," *India Persianate Age*, Aug. 2019, doi: 10.1525/9780520974234.

[15] J. H. L. Goh *et al.*, "Artificial intelligence for cataract detection and management," *Asia-Pacific J. Ophthalmol.*, vol. 9, no. 2, pp. 88–95, 2020, doi: 10.1097/01.APO.0000656988.16221.04.

[16] R. Yin, C. Liu, M. Zhao, S. Yao, and H. Liu, "The implementation and impacts of China's largest payment for ecosystem services program as revealed by longitudinal household data," *Land use policy*, vol. 40, pp. 45–55, 2014, doi: 10.1016/J.LANDUSEPOL.2014.03.002.

[17] A. R. Rojabi, "Exploring EFL Students' Perception of Online Learning via Microsoft Teams: University Level in Indonesia," *English Lang. Teach. Educ. J.*, vol. 3, no. 2, p. 163, Sep. 2020, doi: 10.12928/ELTEJ.V3I2.2349.

[18] P. Eichengreen, B., & Gupta, "Managing sudden stops," *World Bank Econ. Rev.*, vol. 32, no. 2, pp. 361–383, 2018.

[19] G. Vavoulas, M. Pediaditis, E. G. Spanakis, and M. Tsiknakis, "The MobiFall dataset:

An initial evaluation of fall detection algorithms using smartphones," *13th IEEE Int. Conf. Bioinforma. Bioeng. IEEE BIBE 2013*, 2013, doi: 10.1109/BIBE.2013.6701629.

[20] Z. H. & Y. G. Yuren Mao, Yuhang Ge, Yijiang Fan, Wenyi Xu, Yu Mi, "A survey on LoRA of large language models," *Front. Comput. Sci*, vol. 19, pp. 1–140, 2024, doi: https://link.springer.com/article/10.1007/s11704-024-40663-9.

[21] Y. Z. Feifei Zhao, Hui Feng, Haibo Tong, Zhengqiang Han, Enmeng Lu, Yinqian Sun, "Building Altruistic and Moral AI Agent with Brain-inspired Affective Empathy Mechanisms," *arXiv:2410.21882*, 2024, doi: https://doi.org/10.48550/arXiv.2410.21882.

[22] Y. Al Amrani, M. Lazaar, and K. E. El Kadirp, "Random Forest and Support Vector Machine based Hybrid Approach to Sentiment Analysis," *Procedia Comput. Sci.*, vol. 127, pp. 511–520, Jan. 2018, doi: 10.1016/J.PROCS.2018.01.150.

[23] M. I. Azim, "Corporate governance mechanisms and their impact on company performance: A structural equation model analysis," *Aust. J. Manag.*, vol. 37, no. 3, pp. 481–505, Dec. 2012, doi: 10.1177/0312896212451032.

[24] Y. L. Yong TanXi Nan, Jin Liu, Xingchen Xu, "'Generate' the Future of Work through AI: Empirical Evidence from Online Labor Markets," *SSRN*, p. 65, 2023, [Online]. Available: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4529739

[25] T. D. Havlicek and S. R. Carpenter, "Pelagic species size distributions in lakes: Are they discontinuous?," *Limnol. Oceanogr.*, vol. 46, no. 5, pp. 1021–1033, 2001, doi: 10.4319/lo.2001.46.5.1021.

[26] M. Mirhoseini, S. Early, N. El Shamy, and K. Hassanein, "Actively open-minded thinking is key to combating fake news: A multimethod study," *Inf. Manag.*, vol. 60, no. 3, Apr. 2023, doi: 10.1016/J.IM.2023.103761.

[27] P. Rodgers, *Design for people living with dementia*. Accessed: Dec. 25, 2023. [Online]. Available: https://www.routledge.com/Design-for-People-Living-with-Dementia/A-Rodgers/p/book/9780367554750