11th MALAYSIA STATISTICS CONFERENCE 2024
Data and Artificial Intelligence: Empowering the Future
Sasana Kijang, Bank Negara
19th September 2024

Assessing AI-Induced Job Displacement in Malaysia

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Abstract:
This study examines the impact of artificial intelligence (AI) adoption on job displacement in Malaysia. A mathematical model has been developed to estimate job displacement across various occupational categories, considering factors such as the AI job displacement rate and the adoption rate. The analysis projects a total displacement of approximately 1,575,970 workers by 2026 across different occupational categories. High-skill and middle-skill occupations show vulnerability to AI-induced displacement, challenging previous assumptions about automation primarily affecting blue-collar workers. The study emphasizes the need for proactive policies, such as investments in AI education, training, and social safety nets, to prepare the workforce for AI's impact.

Keywords:
Artificial intelligence; job displacement; reskillin; Malaysian labor market

1. Introduction:
Artificial intelligence (AI) has rapidly emerged as a transformative technology with the potential to reshape industries and redefine labor market. The adoption of AI technologies has been growing at an unprecedented rate, particularly after OpenAI released ChatGPT to the public in November 2022. The current AI revolution is driven by advancements in machine learning, data analytics, computational power, and the public availability of large language model (LLM). According to McKinsey's report (2018), AI could contribute to global GDP by about 1.2 percent annually. In Malaysia, the government's National Policy on Industry 4.0, launched in 2018, and Malaysia's National Artificial Intelligence (AI) Roadmap 2021-2025, launched in 2021, both emphasizes the importance of AI and other advanced technologies in driving the nation's industrial transformation.

While AI promises efficiency and innovation, it also poses significant risks of job displacement, particularly in roles that involve repetitive tasks and data processing. Job displacement is often associated to frictional and structural types of unemployment. Frey and Osborne (2013) highlighted that up to 47% of total US employment is at risk due to computerization. This statistic, although based on the US labor market, resonates globally, and indicates similar vulnerabilities in other countries, including Malaysia. The

International Labour Organization (2019) also warns that economies with a significant portion of the workforce engaged in routine manual and cognitive tasks could face substantial employment shifts due to AI and automation

With this concern in mind, the question of how vulnerable are workers in Malaysia to AI becomes pertinent. To answer this question, this study aims to estimate the impact of AI adoption on job displacement in Malaysia. To achieve this objective, a model to estimate job displacement level has been developed (see Section 3) and applied (see Section 4). In the next section, the literature review on the subject is presented.

2. Literature Review:

2.1 Variables and Measures of AI and Automation

Many studies have been conducted on the adoption and impact of artificial intelligence (AI) and automation technologies in various economic sectors. This section presents the common variables used for assessing AI implementation and automation at a micro (e.g. firm), and macro (e.g. national economy) levels. The variables are listed in Table 1 for ease of reference.

Researchers have proposed and empirically tested a wide range of indicators, drawing from established technology adoption models (Davis, 1989; Venkatesh et al., 2003) and developing new frameworks specific to AI and automation (Brynjolfsson & McAfee, 2017; Bughin et al., 2017). For example, at the firm level, variables such as user perceptions, organizational readiness, and the extent of AI integration into business processes are often employed as proxies. Other variables are perceived usefulness, ease of use, and intention to adopt AI-powered services (Ajzen, 1991; Davis, 1989). Indicators of actual usage, user satisfaction, and the number of AI-powered products or services offered are also used in assessing the level of AI adoption within organizations (DeLone & McLean, 2003). For macro analysis, variables used are AI-related investments, and ICT expenditures, and supply of knowledge-workers (Acemoglu & Restrepo, 2018; Frey & Osborne, 2017). The consideration of micro and macro variables shows various levels and ways to measure the impact of AI and automation adoption.

Table 1: Variables for Measuring AI Adoption and Automation

Variable	Micro (Firm)	Macro (Economy)	References
AI Adoption Variables			
Perceived usefulness	✓		Davis (1989); Venkatesh et al. (2003)
Perceived ease of use	✓		Davis (1989); Venkatesh et al. (2003)
Intention to use AI-powered services	✓		Ajzen (1991); Venkatesh et al. (2003)
Actual usage of AI-powered services	✓	✓	DeLone & McLean (2003)
User satisfaction with AI solutions	✓		DeLone & McLean (2003)
AI-related investments	✓	✓	Bughin et al. (2017)

Number of AI-powered products/services	✓	✓	Brynjolfsson & McAfee (2017)
Employee AI literacy and skills	✓	✓	Fountaine et al. (2019)
AI integration across business processes	✓		Davenport & Ronanki (2018)
Frequency of AI-assisted decision-making	✓		Agrawal et al. (2018)
Automation Variables			
Level of process automation	✓		Parasuraman et al. (2000)
Automation rate	✓	✓	Acemoglu & Restrepo (2018)
Time saved through automated processes	✓		Autor (2015)
Error reduction rate in automated tasks	✓		Wickens et al. (2015)
Cost savings from automation, AI investment expenditure	✓	✓	Frey & Osborne (2017)
Number of automated workflows implemented	✓		Davenport & Kirby (2016)
Employee productivity after automation	✓	✓	Brynjolfsson & McAfee (2014)
Customer satisfaction with automated services	✓		Rust & Huang (2014)
ROI for automation projects	✓		Autor et al. (2003)
Scalability of automated systems	✓		Brynjolfsson et al. (2018)

2.2 Impacts of AI and Automation on the Labor Market

There is increasing concern about AI and automation displacing jobs. Bessen (2015) noted that occupations are key to analysis since technology often automates specific tasks, and much human capital is occupation-specific. Frey and Osborne (2013) estimate that 47% of US jobs could be automated within 10 to 20 years. Roux (2018) found that 35% of jobs in South Africa are potentially automatable, while Arntz et al. (2016) estimate an average of 9% across 21 OECD countries. Studies in Finland (Pajarinen and Rouvinen, 2014), Germany (Brzeski and Burk, 2015), and Europe (Bowles, 2014) report similar findings. Carbonero et al. (2020) show robots cause a 5% long-term job decline in emerging countries due to a 24% increase in robotic technology. Balsmeier and Woerter (2019) found that while digital technologies increase high-skilled employment in Swiss firms, they decrease low- and medium-skilled jobs demand.

Conversely, some evidence suggests AI and automation create more jobs than they displace (Autor, 2015; Manyika et al., 2017; Parscheu & Hauge, 2020). For instance, Koch et al. (2019) observed that automation in Spanish manufacturing from 1990–2016 increased employment, attributed to the scale effect. Vermeulen et al. (2018) noted about the ‘creative destruction’ nature of technology, which tends to shake many economic sectors, thus displacing jobs.

In general, many studies suggest that while automation may result in job losses in one sector, it also creates new jobs in another. This effect is known as job displacement. Arntz et al. (2016) argued that the estimated "jobs at risk" should not be equated with actual job losses. Since technological change is slow, workers have time to adjust. Automation also creates inequality in opportunity, with low-qualified workers usually bear higher adjustment costs compared to highly qualified workers.

Frohm et al. (2006) examined the manufacturing sector's views on automation, finding that it enhances efficiency and productivity, leading to cost savings and greater competitiveness. Automation also decreased production time, improved accuracy and repeatability, reduced human errors and labor costs, enhanced safety, and higher production volumes. All these advantages of AI and automation also create new opportunities, thus new jobs.

2.3 Effects of AI and Automation on Malaysian Job Market

Several studies have explored the effects of AI and automation in Malaysia, yet there remains a significant gap in understanding the extent of job displacement due to AI adoption. This section synthesizes key findings from recent studies, highlighting the current state, the challenges faced, and the potential impact on the workforce.

Omar et al. (2017) examined the integration of AI into governance by Malaysian public companies, finding that although AI is beneficial, its adoption is hindered by behavioral and legal challenges. Lee and Tajudeen (2020) investigated AI in the Malaysian accounting sector, noting improvements in productivity and efficiency but also potential job losses due to automation. However, they focused more on organizational benefits than the impact on accountants' employment. Both studies agreed that AI could transform jobs by automating administrative tasks, thus reducing human involvement in some roles.

Lada et al. (2023) explored factors influencing AI adoption by Malaysian SMEs, identifying perceived benefits, government support, and technological readiness as positive factors, while cost, skill shortages, and cybersecurity were major barriers. They suggested training and policies to mitigate job losses. Baki et al. (2023) emphasized the need for technological and social skills to adapt to AI changes. Additionally, Jukin (2024) highlighted the risk of AI exacerbating job market disparities in Malaysia, calling for inclusive policies. Geetha et al. (2024) and Amini and Ravindran (2024) stressed the need for government policies to manage AI's economic and social impacts responsibly.

Even though there has been a lot of studies done on how AI affects jobs around the world, there is a gap in specific studies that measure the amount of job loss caused by AI, particularly in the case of Malaysia. Most studies focus on the advantages and early obstacles of integrating AI, lacking specific figures on the extent of job loss in different industries. This research seeks to bridge this gap by creating a model to estimate the influence of AI on job displacement in Malaysia.

3. Methodology:

The model used to estimate the effect of AI on job displacement is given by Equation (1). This model considers the rate of AI job displacement for different occupation categories, the rate of AI adoption, and the period of adoption, which is expressed as:

$$D_i(t) = L_i \cdot \delta_i \cdot r \cdot t \tag{1}$$

where:

- D_i(t) is the number of displaced workers in occupation category i (i = 1, 2, ..., I)
- L_i is total initial number of workers in occupation category i
- δ_i is the AI-induced job displacement rate for occupation category i (refer to Table 2)
- r is the rate of AI technologic change (assumed at 0.05 per year in this study
- t is the period of AI adoption (in this study, $t = 5$).

The following are the key assumptions for the model:

- The rate of AI adoption (δ_i) is constant over time for each occupation category.
- The impact of AI on job displacement is linear and directly proportional to the rate of AI technological change (r), and the rate of job displacement.
- There is no delay between AI adoption and its impact on job displacement.
- The total number of workers in each occupation category remains constant over the period of analysis.

To estimate the impact of AI adoption, the data for total number of workers according to occupation category (L_i) are gathered from the Department of Statistics Malaysia's report. For information on the rate of AI job displacement for each occupation category (δ_i), the rate is gathered from various relevant studies (refer to Table 2). With the outlined assumptions, and the available information and data, the results of the estimations are presented and discussed in the next section.

Table 2: Coefficient of AI Job Displacement by Occupation Category

Occupation Categories	Job Displacement Rate
High-Skill Occupations	0.67
Middle-Skill Occupations	0.45
Low-Skill Occupations	0.30
Administrative and Managerial Roles	0.55
Professional and Engineering Roles	0.60
Manufacturing Process Occupations	-0.10 (indicating growth potential)
Service and Sales Workers	0.40
Clerical Support Workers	0.50

Sources: Cazzaniga, Pizzinelli, Rockall, & Tavares (2024); PwC (2024); Morikawa (2017)

4. Result: Estimates of Job Displacement Due to AI Adoption

The analysis presented in this section estimate the potential impact of AI on various occupational categories in Malaysia, based on the AI job displacement rate, and workforce data from 2021. The estimation of AI-induced job displacement is based on Equation (1). The results in Table 3 show a significant impact across different occupational categories, with a total projected displacement of approximately 1,575,970 workers by 2026. AI fundamentally affects all categories of occupations.

High-skill occupations, such as managerial and professional roles are the most displaced by AI. Managers, with a displacement rate of 0.55, are estimated to see a displacement of 81.98 thousand workers by 2026. Professionals, with a displacement rate of 0.60, are projected to experience the displacement of 295.05 thousand workers. The higher displacement coefficients in these categories can be attributed to the increasing capabilities of AI in performing complex analytical tasks, decision-making, and management processes traditionally performed by humans. While previous studies (Frey & Osborne, 2013) showed that job displacement due to automation and robotics primarily affected blue-collar workers, generative AI is more detrimental to white-collar workers.

Table 3: AI-Induced Job Displacement in Malaysia by Occupation Category

Occupation	Total Number of Workers Employed (2021) ('000)	Coefficient of AI Job Displacement	Workers Displaced After 5 Years ('000)
Managers	594.10	0.55	81.98
Professionals	1,967.00	0.60	295.05
Technicians and associate professionals	1,695.60	0.45	190.77
Clerical support workers	1,704.60	0.50	213.08
Service and sales workers	3,822.80	0.40	382.28
Skilled agricultural, forestry, livestock and fishery workers	695.10	0.30	52.13
Craft and related trades workers	1,284.80	0.30	96.36
Plant and machine-operators and assemblers	1,637.10	0.30	122.78
Elementary occupations	1,873.80	0.30	140.54
TOTAL	**15,274.90**		**1,575.97**

For middle-skill jobs there are also notable displacement risks. With a displacement rate of 0.45, technicians and associate professional category is expected to lose 190.77 thousand jobs in a five-year period. Clerical support workers (displacement rate = 0.50), face a projected displacement of 213.08 thousand workers within the same period. The significant displacement impact on these occupations implies AI's ability in improving further existing state of automation, thus affecting the middle-skill occupations.

The displacement impact on low-skill occupations is relatively lower compared to high and middle-skill jobs. Categories such as service and sales workers, skilled agricultural, forestry, livestock and fishery workers, craft and related trades workers, plant and machine operators and assemblers, and elementary occupations have displacement rates ranging from 0.30 to 0.40. These categories collectively face a displacement of approximately 834.09 thousand workers. While manual tasks less susceptible to AI and full automation, the AI-improved automation of processes can still lead to significant job reductions. For instance, service and sales workers are estimated to see a displacement of 382.28 thousand jobs, reflecting AI's growing role in customer service, sales analytics, and transaction processing.

5. Discussion and Conclusion:

Artificial intelligence (AI) and automation are transforming various sectors and reshaping the labor market in Malaysia. This study has estimated the levels of job displacement due to AI adoption in the country. In general, the analysis shows that AI adoption has varying degrees of job displacement effects across different occupation categories. High-skill and middle-skill occupations are particularly vulnerable to the AI revolution relative to low-skill jobs. Targeted interventions to prepare the workforce for the future is therefore, urgent.

To mitigate the adverse effects of AI on employment, investment in education and training tailored to enhance AI and digital literacy and technical skills is crucial. Education and training curriculum should focus on nurturing new experts in AI, while at the same time reskilling and upskilling the existing workforce to transition to new roles created by AI and automation technologies. Social safety nets should also be strengthened to provide supports and opportunities to displaced workers, such as worker-training initiatives and subsidies, job placement services, and mental health support, which can help ease the transition for affected individuals. New strategies and policies should be devised to adapt to the rapidly changing technologies so that this country can lead, grow and seize new opportunities without being left behind.

6. References:

1. Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review, 108*(6), 1488-1542.
2. Agrawal, A., Gans, J., & Goldfarb, A. (2018). *Prediction machines: The simple economics of artificial intelligence*. Harvard Business Press.
3. Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211.
4. Amini, M., & Ravindran, L. (2024). A review on the social impacts of automation on human capital in Malaysia. *Machine Intelligence in Mechanical Engineering*, 327-342.
5. Arntz, M., Gregory, T., & Zierahn, U. (2016). The risk of automation for jobs in OECD countries: A comparative analysis. *OECD Social, Employment and Migration Working Papers*.
6. Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives, 29*(3), 3-30.
7. Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics, 118*(4), 1279-1333.
8. Billmeier, B., & Woerter, M. (2019). Is this time different? How digitalization influences job creation and destruction. *Research Policy, 48*(8), 1-1.
9. Baki, N. U., Rasdi, R. M., Krauss, S. E., & Omar, M. K. (2023). Employee Competencies in the Age of Artificial Intelligence: A Systematic Review from Southeast Asia. *International Journal of Academic Reserach in Economics and Management Sciences*, *12*(1).
10. Bessen, J. (2019). Automation and jobs: When technology boosts employment. *Boston University School of Law, Law and Economics Research Paper No. 17-09*.
11. Bowles, J. (2014). The computerization of European jobs. *Bruegel, Brussels*.

12. Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W. W. Norton & Company.
13. Brynjolfsson, E., & McAfee, A. (2017). The business of artificial intelligence. *Harvard Business Review, 95*(4), 3-11.
14. Brynjolfsson, E., Rock, D., & Syverson, C. (2018). Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. In *The economics of artificial intelligence: An agenda* (pp. 23-57). University of Chicago Press.
15. Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., Dahlström, P., ... & Trench, M. (2017). Artificial intelligence: The next digital frontier? *McKinsey Global Institute*.
16. Carbonero, F., Ernst, E., & Weber, E. (2020). Robots worldwide: The impact of automation on employment and trade. *Beiträge zur Jahrestagung des Vereins für Socialpolitik 2020*.
17. Davenport, T. H., & Kirby, J. (2016). *Only humans need apply: Winners and losers in the age of smart machines*. Harper Business.
18. Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review, 96*(1), 108-116.
19. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340.
20. DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems, 19*(4), 9-30.
21. Department of Statistics Malaysia. (2021). Labour market review, Q3 2021. Department of Statistics, Malaysia.
22. Fountaine, T., McCarthy, B., & Saleh, T. (2019). Building the AI-powered organization. *Harvard Business Review, 97*(4), 62-73.
23. Frey, C. B., & Osborne, M. A. (2013). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change, 114*, 254-280.
24. Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change, 114*, 254-280.
25. Frohm, J., Lindstrom, V., Winroth, M., & Stahre, J. (2006). The industry's view on automation in manufacturing. *IFAC Proceedings Volumes, 39*(2), 453-458.
26. Cazzaniga, N., Pizzinelli, C., Rockall, K., & Tavares, M. M. (2024). Gen-AI: Artificial Intelligence and the Future of Work. IMF Staff Discussion Notes, 2024(001). International Monetary Fund.
27. Jukin, N. A. F. (2024). Inclusive Strategies for AI-Driven Employment in Malaysia: Decentralization, Policy Interventions, and Collaborative Governance. *Policy Interventions, and Collaborative Governance (April 24, 2024)*.
28. Koch, M., I., M. (2021). Robots and firms. *The Economic Journal, 131*(636), 2553-2584.
29. Lada, E., H., S., & Tajudeen, I. (2023). Artificial intelligence adoption among Malaysian SMEs. *Journal of Technology and Society, 45*(1), 29-40.
30. Lada, S., Chekima, B., Karim, M. R. A., Fabeil, N. F., Ayub, M. S., Amirul, S. M., & Zaki, H. O. (2023). Determining factors related to artificial intelligence (AI) adoption among Malaysia's small and medium-sized businesses. *Journal of Open Innovation: Technology, Market, and Complexity*, *9*(4), 100144.
31. Lee, C. S., & Tajudeen, F. P. (2020). Usage and impact of artificial intelligence on accounting: Evidence from Malaysian organisations. *Asian Journal of Business and Accounting*, 13(1).
32. Manyika, J., Lund, S., Chui, M., Bughin, J., Woetzel, J., Batra, P., Sanghvi, S. (2017). Jobs lost, jobs gained: What the future of work will mean for jobs, skills, and wages. *McKinsey Global Institute*.

33. McKinsey & Company. (2019, December 1). The impact and opportunities of automation in construction. Retrieved from McKinsey & Company: https://www.mckinsey.com/business-functions/operations/our-insights/the-impact-and-opportunities-of-automation-in-construction
34. McKinsey Global Institute. (2017). A future that works: Automation, employment and productivity. *McKinsey & Company*.
35. Ministry of Human Resources. (2020). Malaysia standard classification of occupations. https://www.mohr.gov.my/pdf/masco/MASCO_2020_BI_Edaran.pdf
36. Morikawa, M. (2017). Who are afraid of losing their jobs to artificial intelligence and robots? Evidence from a survey. GLO Discussion Paper, No. 71. Global Labor Organization (GLO).
37. National Policy On Industry 4.0: https://www.malaysia.gov.my/portal/content/31224
38. Omar, S. A., Hasbolah, F., & Ulfah, M. Z. (2017). The diffusion of artificial intelligence in governance of public listed companies in Malaysia. *International Journal of Business, Economics and Law*, *14*(2), 1-9.
39. Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans, 30*(3), 286-297.
40. Pajarinen, M., & Rouvinen, P. (2014). Computerization threatens one third of Finnish employment. *ETLA Brief, 22*, 13.
41. Parschau, C., & Hauge, J. (2020). Is automation stealing manufacturing jobs? Evidence from South Africa's apparel industry. *Geoforum, 120*, 120-131.
42. PWC. (2024). PwC's 2024 global AI jobs barometer. Retrieved from https://www.pwc.com/gx/en/news-room/press-releases/2024/pwc-2024-global-ai-jobs-barometer.html
43. Rust, R. T., & Huang, M. H. (2014). The service revolution and the transformation of marketing science. *Marketing Science, 33*(2), 206-221.
44. Sorgner, A. (2017). The automation of jobs: A threat for employment or a source of new entrepreneurial activity. *Foresight and STI Governance, 11*(3), 37-48.
45. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478.
46. Wickens, C. D., Hollands, J. G., Banbury, S., & Parasuraman, R. (2015). *Engineering psychology and human performance*. Psychology Press.