JURNAL AKUNTANSI KEUANGAN DAN BISNIS (JAKB)
Vol 9, No.1, December 2025 – May 2026
Page. 57-69
Website Jurnal: https://jurnal.pcr.ac.id/index.php/jakb doi: 10.35143/jakb.v19i1.6934

AI Automation and Labor Dynamics in Indonesian Palm Oil: Job Displacement and Skill Upgrading

Euis Eka Pramiarsih[a], Galih Ariprayugo[b*], Gelar Abifadilla[c]
[a,c] Post Graduate School, Universitas Langlangbuana, Jl Karapitan No.116, Bandung, Jawa Barat 40261, Indonesia
[b] Faculty of Business and Economics, Universiti Malaya, 50603 Kuala Lumpur, Malaysia
***Corresponding Author:** galihariprayugo25@gmail.ac.id

Received: 08 April 2026 | **Revised**: 30 May 2026 | **Accepted**: 31 May 2026| **Published**: 31 May 2026

A B S T R A C T

Main Purpose - This study explores artificial intelligence (AI) automation's dual impact on Indonesian palm oil labor dynamics, emphasizing the job displacement and skill upgrading interplay.
Method - This study used a Systematic Literature Review (SLR) with PRISMA 2020 guidelines to analyze 25 peer-reviewed articles from Scopus and Web of Science, supported by grey literature from sources such as the WEF and ILO. The articles were selected, screened, and analyzed systematically using thematic synthesis.
Main Findings - AI-driven harvest automation may reduce the need for low-skilled manual workers, but it will increase demand for workers with technical skills and green ESG competencies. At the same time, AI can help plantations overcome labor shortages by supporting a shrinking plantation workforce. However, its adoption requires inclusive EaaS models for smallholders, better infrastructure, strong data governance, and gender-inclusive workforce policies.
Theory and Practical Implications - This study combines the Technology-Organization-Environment (TOE) framework and Skill-Biased Technological Change (SBTC) theory to explain how technology affects skills and work in agribusiness. In practice, the Pentahelix matrix offers strategies for government, universities, industry, communities, and media to reduce unemployment risks, protect data privacy, and support an inclusive workforce transition.
Novelty - This research contributes to contextualizing global agricultural automation discourse within the Indonesian palm oil sector, positioning AI as a vital catalyst for workforce evolution amidst pronounced demographic and structural challenges.

Keywords: artificial intelligence, data governance, job displacement, palm oil, skill upgrading

1. INTRODUCTION

The palm oil industry represents a strategic component of the global agricultural economy, with Indonesia occupying a central position in this sector. According to the Indonesia Permanent Estate Crops Statistics 2024, palm oil is the country's leading estate crop, covering approximately 16.01 million hectares and contributing around 56–60% of global palm oil supply. This position makes Indonesia a key actor in supporting global food, energy, and oleochemical systems (BPS, 2024a, 2024b). The sector is operated by both smallholders and large-scale corporate plantations, particularly in major producing provinces such as Riau, North Sumatra, and Central Kalimantan (BPS, 2024a, 2024b). These corporate plantations play an important role in sustaining Indonesia's position as the world's largest palm oil producer. However, despite its substantial economic contribution and global significance, the Indonesian palm oil industry remains highly dependent on labor-intensive production practices, especially for daily operational activities such as harvesting, pruning, and fertilizer application.

Alongside its strong global position, the Indonesian palm oil industry is increasingly confronted with a chronic labor shortage driven by demographic and socio-economic changes. The aging agricultural workforce, combined with rural-to-urban migration among younger workers, has reduced the availability of labor for physically demanding estate activities, particularly harvesting. This condition is further intensified by the low social prestige often associated with plantation work, making the sector less attractive to younger generations. As a result, labor scarcity has become a critical operational challenge that directly affects harvesting efficiency, fresh fruit bunch collection, and overall plantation productivity. Regional studies show that unharvested fresh fruit bunches caused by labor shortages can generate substantial annual financial losses, highlighting the urgency of mechanized and technology-based interventions(Faudzi & Bakri, 2023; Rannando et al., 2025; Thaddeus et al., 2023). In response to these pressures, Indonesian plantation companies have begun adopting Logistics 4.0 and smart agriculture technologies, including artificial intelligence and robotic automation, to sustain productivity under changing labor conditions (Osuna-Velarde et al., 2023). These technologies offer a strategic pathway for maintaining operational continuity while supporting a broader structural transformation of the plantation workforce.

The adoption of AI-based technologies in agriculture has generated a complex socio-economic debate regarding labor sustainability, particularly in labor-intensive plantation systems. In the palm oil sector, AI applications range from image recognition systems for sorting fresh fruit bunches to autonomous harvesting robots designed to improve operational efficiency (Judijanto, 2026; Lai et al., 2023; Yang et al., 2021). However, unlike mechanized grain farming in temperate regions, Indonesian palm oil plantations face more complex deployment conditions, including unstructured terrain, remote plantation locations, and the irregular geometry of fresh fruit bunches, which make AI implementation technically challenging and socially consequential for local labor communities (Faudzi & Bakri, 2023; Ismail et al., 2023). On the one hand, automation may reduce the demand for low-skilled manual labor, raising concerns over job displacement, forced rural labor transition, and potential disruption to the livelihoods of rural communities that depend on plantation employment (Yu et al., 2024). On the other hand, AI adoption may also create new forms of employment that require higher technical capabilities, such as drone operation, AI system maintenance, machine supervision, and yield data analysis, reflecting a process of skill upgrading within plantation labor structures.

Although previous studies have shown that AI and robotic automation can generate both labor substitution and labor creation effects, empirical evidence remains concentrated in developed economies and in China's agricultural context. Yang et al. (2024), for instance, documented the dual substitution and creation effects of AI on agricultural labor using province-level panel data in China, while Yu et al. (2024) found that a 1% increase in urban robot density increases the probability of rural labor re-migration by 0.249%. However, these labor dynamics remain insufficiently examined in Southeast Asian plantation agriculture, particularly in Indonesia's palm oil sector (Anas et al., 2025; Jelsma et al., 2019; Mukhlis et al., 2025). This gap is important because Indonesia's palm oil industry differs from other agricultural systems due to its smallholder-dominated structure, chronic labor scarcity, geographically dispersed plantation areas, and distinct socio-economic dependence on plantation work. Therefore, the mechanisms through which AI-driven automation reshapes labor demand, skill requirements, rural employment stability, and inclusive workforce transition in Indonesia's palm oil plantation system remain critically underexplored in the existing literature.

To address this research gap, this study examines how AI and robotic automation reshape labor dynamics in Indonesian palm oil plantations by focusing on three key issues: job displacement and rural labor transfer among low-skilled workers, emerging skill requirements and universal competencies required for AI-enabled plantation work, and the role of environmental, infrastructural, and financial barriers in mediating the socio-economic outcomes of AI adoption. Specifically, this study aims to analyze the extent to which AI-driven automation substitutes routine manual labor and how this substitution pressure may accelerate structural rural-to-urban labor migration by reducing employment opportunities in plantation regions. It also seeks to identify emerging technical competencies, including AI system operation, drone agronomy, and precision data analysis, that are increasingly required as plantation work shifts toward more technology-intensive practices. In addition, this study evaluates the barriers that shape AI implementation in corporate palm oil estates, particularly those related to infrastructure readiness, investment capacity, environmental conditions, and organizational preparedness. Using a Systematic Literature Review approach, this paper ultimately develops a comprehensive conceptual framework to explain the dual impact of AI on labor dynamics in Indonesian agribusiness, particularly its role in simultaneously displacing routine manual work and creating demand for higher-skilled technical employment.

2. RESEARCH METHODS

This conceptual study employs a Systematic Literature Review (SLR) approach, adhering strictly to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines (Page et al., 2021). The structured methodology ensures rigor, transparency, and reproducibility in synthesizing the existing literature regarding AI's socio-economic impact on agricultural labor dynamics. To ensure the conceptual framework captures real-world industry dynamics, this SLR is supplemented by authoritative grey literature from organizations such as the WEF, ILO, and CIPS, included to capture real-world industry dynamics beyond the peer-reviewed literature.

To establish a comprehensive foundation for a reliable systematic literature review, the search for relevant articles was conducted exclusively within the Scopus and Web of Science (WoS) databases. The rationale for this methodological choice is grounded in the extensive and interdisciplinary coverage of these databases, which index a vast body of literature across the sciences, social sciences, arts, and humanities.

The study identification process was conducted in accordance with the PRISMA 2020 framework (Page et al., 2021), encompassing the phases of identification, screening, and eligibility. The Identification phase established a broad but targeted record pool; the Screening phase removed irrelevant records efficiently at title and abstract level; and the Eligibility phase ensured only studies with direct socio-economic relevance to agricultural labor dynamics were retained, preventing dilution of findings with purely technical engineering literature. The initial step involved establishing primary keywords and their related terms, which were subsequently used to construct the search strings detailed in Table 1. Executing this search strategy across both databases resulted in the retrieval of 450 records. The entire article selection workflow is visually detailed in the PRISMA diagram presented in Figure 1.

Table 1. Database Search String

Database	Search String
WoS & Scopus	("Artificial Intelligence" OR "Automation" OR "Robotics") AND ("Palm Oil" OR "Agriculture" OR "Agribusiness") AND ("Labor Dynamics" OR "Job Displacement" OR "Skill Upgrading" OR "Rural Transfer").

Source: Author(s) works

To ensure that the selected literature directly addressed the research questions and met the required academic standards, this study established specific inclusion and exclusion criteria prior to the screening process. The included studies were limited to publications issued between 2014 and 2026, written in English or Bahasa Indonesia, and published as peer-reviewed journal articles, conference papers, review articles, or relevant industry reports. In terms of technological focus, the review included studies examining the socio-economic impacts of AI and automation on labor, employment transition, and human resource management in agriculture. The domain was also restricted to the agricultural sector, with particular attention to large-scale estate crops such as palm oil or equivalent agribusiness models. Conversely, studies published before 2014, non-English and non-Indonesian publications, opinion pieces, blogs, news articles, non-academic reports, patents, and studies focusing solely on technical or mechanical engineering aspects without socio-economic relevance were excluded. Studies from non-agricultural sectors, such as manufacturing and healthcare, were also excluded to maintain the thematic focus of the review.

The study selection process followed the PRISMA 2020 flow procedure to ensure transparency, reproducibility, and systematic documentation at each stage of article selection. During the identification stage, the database search produced 450 potential records from the selected academic databases. After removing 120 duplicate records using reference management software, 330 articles proceeded to the screening stage. At this stage, the titles and abstracts were independently reviewed by the researchers, resulting in the exclusion of 250 articles that were not directly relevant to the thematic focus of the study. To strengthen the reliability of the screening process, any disagreement regarding article inclusion was resolved through structured discussion between the two reviewers. When disagreement persisted, a third reviewer was consulted to reach a final decision, thereby ensuring transparency and improving inter-rater reliability.

In the eligibility stage, the full texts of the remaining 80 articles were assessed comprehensively against the predefined inclusion and exclusion criteria. From this process, 55 articles were excluded, mainly because they focused exclusively on the technical engineering aspects of AI or robotics without addressing socio-economic, labor, or human resource implications. Ultimately, 25 high-quality peer-reviewed articles met all criteria and were selected as the primary literature foundation for this study. This final pool of articles provided the basis for understanding how AI-driven automation affects labor displacement, skill upgrading, adoption barriers, and inclusion within agricultural and plantation-based contexts.

A quality assessment was then conducted on the final articles by adapting the principles of the Critical Appraisal Skills Programme. Each article was evaluated based on three main dimensions: the clarity and rigor of the research methodology, relevance to agribusiness labor dynamics, and validity of the findings. Articles that did not meet an acceptable threshold in terms of methodological clarity or thematic relevance were excluded from the final synthesis. This stage ensured that the conceptual framework developed in this study was based only on reliable and relevant evidence. After the quality assessment, the extracted data were analyzed using thematic synthesis, in which the findings were systematically coded and grouped into four main themes: displacement, skill upgrading, barriers, and inclusion.

In the subsequent stage, qualitative content analysis was conducted on the 25 selected articles to identify recurring patterns and conceptual relationships within the literature (Lee & Abdullah, 2024). The analysis involved a structured coding process in which key findings from each article were extracted, categorized, and compared across studies. The synthesis showed that robot applications may increase rural labor re-migration through substitution effects, particularly among low-skilled agricultural workers (Yu et al., 2024). In the palm oil context, sustainable employment transition requires green job creation that integrates technical agricultural skills, digital capabilities, and learning agility (Judijanto, 2026). In addition, robotics has been identified as essential for maintaining operational continuity in Southeast Asia’s palm oil industry, particularly because labor shortages can lead to substantial unharvested fresh fruit bunch losses (Faudzi & Bakri, 2023). However, the implementation of robotics in palm oil plantations remains constrained by complex terrain, limited power access, and coordination challenges, which may reduce the effectiveness of automation deployment (Ismail et al., 2023). Together, these synthesized findings provide the empirical foundation for developing the conceptual framework of this study.

3. RESULT AND DISCUSSION

In the Indonesian palm oil sector, the most immediate risk of job displacement is likely to affect harvesters and manual upkeep workers, whose tasks remain highly dependent on routine physical labor. As AI-powered autonomous vehicles and robotic harvesting systems become increasingly capable of identifying, selecting, and harvesting fresh fruit bunches, the demand for low-skilled manual labor may gradually decline. This shift is driven not only by cost-efficiency considerations, but also by the operational advantages of AI-based systems, which can work continuously, reduce fatigue-related errors, and improve harvesting precision. Empirical evidence from Yang et al. (2024) shows that a 1% increase in AI capital stock reduces low-skilled agricultural labor employment by 0.205%, with the strongest effects occurring in routine and physically intensive tasks similar to those found in Indonesian palm oil operations. This pattern is consistent with the Future of Jobs Report 2025, which identifies routine manual agricultural occupations as highly vulnerable to displacement through machine learning and automation (WEF, 2025). In line with Yu et al. (2024), the adoption of agricultural robots may also intensify rural labor transfer, as workers displaced from plantation regions such as Riau and North Sumatra may be pushed either toward urban labor markets or into other low-skilled informal jobs. This transition creates a significant socio-economic risk because plantation employment remains a major source of rural livelihood, particularly in palm oil-producing regions, and without inclusive transition policies, automation may deepen rural employment vulnerability and worsen the decent work deficits highlighted by the ILO (2022).

At the same time, AI automation also creates demand for higher-skilled labor in palm oil plantations. AI-integrated plantations require new hybrid roles, such as drone agronomists for plantation mapping, data analysts for predictive yield modeling, and AI harvesting supervisors for robotic system maintenance (Hadouga, 2023). This skill upgrading supports corporate ESG targets because precision agriculture using UGVs and drones enables more accurate fertilizer and pesticide application, reduces environmental degradation, and strengthens compliance with ISPO/RSPO standards. Therefore, the transition toward sustainable and digitized palm oil employment requires competency-based approaches that combine agricultural knowledge, digital skills, and environmental stewardship to support green job creation (Judijanto, 2026). This trend is consistent with the WEF (2025), which projects rising demand for AI and Big Data specialists across primary industries, and with Skill-Biased Technological Change theory, which explains that technological advancement increases demand for high-skilled labor while reducing returns to routine manual work (Acemoglu & Restrepo, 2019). Yang et al. (2024) provide empirical support for this pattern by showing that AI capital accumulation creates employment gains for graduate-level high-skilled workers (+0.138%), even as it displaces low- and medium-skilled workers.

However, in the context of Southeast Asian palm oil, AI adoption should not be understood merely as a cost-cutting strategy. The literature suggests that automation is also driven by structural labor shortages rooted in broader socio-economic changes, including an aging plantation workforce, rural-to-urban migration among younger workers, the low social prestige and physical intensity of estate work, and disruptions to foreign labor supply chains during the COVID-19 pandemic (Ismail et al., 2023). This condition is reinforced by decent work deficits in agricultural employment across the Asia-Pacific region, which further reduce workers' willingness to remain in manual plantation roles (ILO, 2022). As rural youth increasingly shift toward urban employment, plantation companies face a growing risk of unharvested crops, particularly in labor-intensive harvesting activities. Faudzi and Bakri (2023) similarly emphasize that dependence on manual labor has long been a major bottleneck in palm oil production, where labor shortages can lead to unharvested fresh fruit bunches and operational losses. In this sense, AI functions as both a substitutive and complementary force: it replaces certain manual tasks while also filling labor gaps that are already present and potentially improving the safety, dignity, and technological quality of agricultural work.

Despite this potential, AI adoption in Indonesian palm oil plantations remains constrained by environmental, infrastructural, and financial barriers (Aroba & Rudolph, 2024). The physical conditions of palm oil estates, including unstructured terrain, remote locations, and limited access to power and communication networks, require sophisticated Unmanned Ground Vehicles capable of operating in complex field environments (Ismail et al., 2023). Weak rural digital infrastructure and limited internet connectivity also restrict the real-time data transmission needed for IoT- and AI-based systems, while poor digital literacy further slows technological adoption in Southeast Asian agriculture (Broløs & Taylor, 2023). In addition, the high capital expenditure required for AI implementation means that adoption is more feasible for large-scale corporate plantations than for independent smallholders (BPS, 2024b). This condition may widen the economic gap within the sector, particularly as corporate plantations are increasingly pressured to adopt traceability technologies to comply with ISPO and RSPO certification standards (Pareira, 2023).

To reduce this technological gap, the literature suggests the adoption of Equipment-as-a-Service or Drone-as-a-Service models. This approach is particularly relevant in Indonesia, where independent smallholders manage more than 40% of palm oil plantations and often lack the capital required to adopt AI-based technologies independently. Without such inclusive models, AI adoption may create a dual-tier industry in which large corporate estates become increasingly efficient while smallholders remain dependent on labor-intensive and less productive practices. Through local cooperative networks, such as Koperasi Unit Desa, EaaS providers can offer shared access to technologies such as harvesting UGVs and precision-spraying drones, along with technical support and data analysis services. This model can lower entry barriers and ensure that the productivity benefits of Agriculture 4.0 are distributed more equitably across the palm oil sector. Evidence from Southeast Asian agriculture, including drone service cooperatives in Thailand’s rice sector and digital advisory cooperatives in Indonesia, suggests that cooperative-based technology sharing is practically feasible and scalable (Voutier & Woo, 2021).

Beyond economic access, AI integration in Indonesian palm oil plantations also introduces socio-ethical challenges. One critical issue concerns its gendered impact. Women constitute an important segment of the plantation workforce, particularly in maintenance activities, fertilizer application, and loose fruit collection (*brondolan*). These tasks are generally repetitive, rule-based, and physically intensive, making them highly susceptible to robotic automation (Moutik, 2025). As a result, AI adoption may disproportionately displace female workers, especially because their current roles offer fewer transition pathways into supervisory or machine-operation positions compared with male harvesters. This risk is intensified by unequal access to digital literacy programs and reskilling opportunities across Southeast Asian agricultural contexts (Broløs & Taylor, 2023; Liang et al., 2025). Therefore, AI implementation without gender-responsive planning may deepen existing labor market inequalities rather than create inclusive transformation. As emphasized through the AI-facilitated Gender Empowerment Ecosystem framework, AI adoption should be accompanied by deliberate efforts to ensure women’s access to digital training, reskilling pathways, and emerging technology-based roles in plantation work (Moutik, 2025).

Another important socio-ethical concern relates to agricultural data governance. The use of IoT sensors, unmanned ground vehicles, and autonomous drones generates large volumes of granular plantation data, including topographical information, localized yield predictions, input-use patterns, and worker productivity indicators. Without a transparent regulatory framework, these data may become concentrated in the hands of large corporate plantations or foreign technology providers, creating risks of data monopolization and information asymmetry. Such conditions may place smallholders and independent farmers at a disadvantage in price negotiation, certification compliance, and supply-chain integration. Moreover, if AI systems improve their predictive accuracy through localized plantation data but the resulting knowledge remains proprietary, the wider agricultural community may not benefit from technological advancement. Therefore, a fair AI transition in palm oil requires an agricultural data governance framework that protects farmers' data rights, prevents excessive concentration of digital power, and promotes collaborative innovation across corporate plantations, smallholders, cooperatives, technology providers, and regulators.

Based on the synthesis of the identified themes, this study proposes a conceptual framework to explain the dual impact of AI adoption on labor dynamics in Indonesian palm oil agribusiness. The framework is presented in Figure 1.

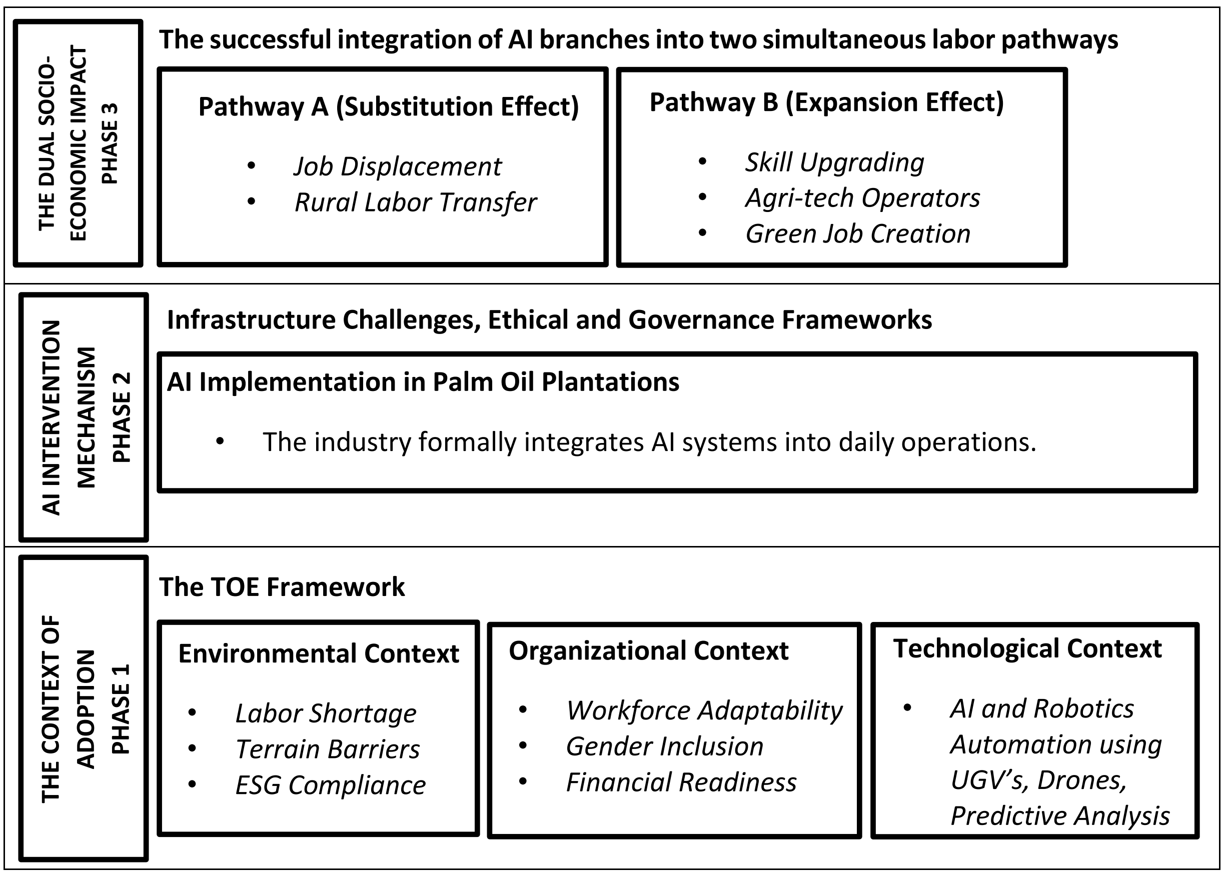

Figure 2. Conceptual Framework

The framework integrates the Technology–Organization–Environment framework to explain the contextual conditions that shape AI adoption and Skill-Biased Technological Change theory to interpret its socio-economic labor outcomes. Conceptually, the framework is structured into three interconnected phases. The first phase captures the adoption context, including environmental pressures such as labor shortages, terrain barriers, and ESG compliance; organizational factors such as workforce adaptability, gender inclusion, and financial readiness; and technological factors such as AI-robotics automation using UGVs, drones, and predictive analytics. The second phase represents the intervention stage, in which AI systems are formally integrated into daily plantation operations, while their success depends on the ability of firms and stakeholders to overcome infrastructure challenges and establish ethical and governance frameworks. The third phase explains the dual socio-economic outcomes of AI adoption, consisting of a substitution pathway that may reduce demand for routine manual labor and intensify rural labor transfer, and an expansion pathway that creates new opportunities for skill upgrading, agri-tech operators, and green job creation.

Table 2. Conceptual Framework Details

Phase	Details
1	• Environmental Context: Demographic shifts (aging workforce and youth migration) create a severe Labor Shortage. Additionally, external pressures such as the mandate for ESG compliance (ISPO/RSPO) drive the need for precision agriculture (Pareira, 2023). Unstructured terrain acts as a physical barrier. • Organizational Context: Corporate plantations rely on their financial readiness (CAPEX) to initiate adoption. Conversely, smallholders rely on alternative models like Equipment-as-a-Service (EaaS) to participate in this digital transition. • Technological Context: The availability and rapid advancement of AI and Robotic Automation (UGVs, drones, predictive analytics) provide the technological intervention capable of replacing routine labor and gathering vast amounts of agricultural data.
2	The industry formally integrates AI systems into daily operations. The success of this phase depends heavily on overcoming infrastructural barriers (e.g., internet connectivity) and establishing robust ethical frameworks (gender inclusion and data governance).
3	Consistent with global macroeconomic projections (WEF, 2025), the successful integration of AI branches into two simultaneous labor pathways: • Pathway A (Substitution Effect): Decreased demand for manual, routine tasks lead to Job Displacement. For vulnerable populations (such as female manual workers), these risks deepening decent work deficits (ILO, 2022) and results in forced Rural Labor Transfer. • Pathway B (Expansion Effect): Increased demand for technological maintenance and farm data analysis drives Skill Upgrading, fostering the emergence of skilled Agri-tech Operators and contributing to inclusive green job creation. Pathway A directly informs RQ1 on job displacement and rural labor transfer; Pathway B responds to RQ2 on emerging skill requirements and workforce upgrading.

Source: Author(s) works

4. CONCLUSION

This study concludes that AI automation in Indonesian palm oil plantations creates a dual labor impact by substituting routine manual work while generating demand for higher-skilled green and digital competencies, with this transition strongly shaped by infrastructural, financial, organizational, and socio-ethical barriers. The findings show that AI adoption may accelerate rural labor transfer and worsen decent work deficits if displaced workers are not supported through inclusive reskilling policies, while at the same time creating new opportunities for agritech operators, data analysts, drone agronomists, and other technology-based plantation roles. By integrating the TOE framework and SBTC theory, this study contributes a contextual conceptual model that explains how AI adoption in palm oil agribusiness is not merely a technological shift, but a structural transformation requiring inclusive Equipment-as-a-Service models, gender-responsive workforce policies, and robust agricultural data governance to prevent smallholder marginalization and ensure equitable benefits. However, this study is limited by its reliance on secondary literature and conceptual synthesis without primary field data; therefore, future studies should conduct surveys, longitudinal case studies, and policy evaluations involving Indonesian plantation workers, female laborers, smallholders, and corporate estates to empirically validate the proposed framework and assess the practical feasibility of AI-driven inclusive transformation.

ACKNOWLEDGEMENT

The authors would like to express their sincere gratitude to Politeknik Caltex Riau and Jurnal Akuntansi Keuangan dan Bisnis (JAKB) as well as all parties who directly contributed to and supported the successful completion of this research.

REFERENCES

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy, 128*(6), 2188–2244. https://doi.org/10.1086/705716

Ahmed, N., Ismail, Z., Ahmad, N., & Othman, M. S. (2022). Expert systems in oil palm precision agriculture: A decade systematic review. *Journal of King Saud University – Computer andInformationSciences,34*(4),1569–1594. https://doi.org/10.1016/j.jksuci.2022.02.006

Akhtar, M. N., Ansari, E., Alhady, S. S. N., & Bakar, E. A. (2023). Leveraging advanced remote sensing and artificial intelligence technologies to manage palm oil plantations: A review. *Agriculture, 13*(2), 504. https://doi.org/10.3390/agriculture13020504

Almtireen, N., & Ryalat, M. (2026). Robotics in precision agriculture: Task-, platform-, and evaluation-oriented review. *Robotics, 15*(4), 81. https://doi.org/10.3390/robotics15040081

Anas, K., Naping, H., Salman, D., & Tenriawaru, A. N. (2025). Differences in assets, strategies, and livelihood outcomes among oil palm smallholder typologies in West Sulawesi, Indonesia. *Sustainability*. https://doi.org/10.3390/su17136064

Aroba, O. J., & Rudolph, M. (2024). Systematic literature review on the application of precision agriculture using artificial intelligence by small-scale farmers in Africa and its societal impact. *Journal of Infrastructure, Policy and Development, 8*, 72–88. https://doi.org/10.24294/jipd8872

Badan Pusat Statistik. (2024a). *Direktori perusahaan perkebunan kelapa sawit Indonesia 2024*. https://www.bps.go.id

Badan Pusat Statistik. (2024b). *Statistik tanaman perkebunan tahunan Indonesia 2024 (Indonesia permanent estate crops statistics 2024)*. https://www.bps.go.id

Broløs, A., & Taylor, E. B. (2023). *Digital change in Southeast Asian agriculture*. Australian Centre for International Agricultural Research (ACIAR). https://www.aciar.gov.au

Hadouga, H. (2023). Leadership in agriculture: Artificial intelligence for modelling and forecasting growth in the industry. *Business Ethics and Leadership, 7*(3), 13–19. https://doi.org/10.61093/bel.7(3).13-19.2023

Hamrani, A., Allouhi, A., Bouarab, F. Z., & Jayachandran, K. (2025). AI and robotics in agriculture: A systematic and quantitative review of research trends (2015–2025). *Crops, 5*(5), 75. https://doi.org/10.3390/crops5050075

International Labour Organization. (2022). *Asia-Pacific sectoral labour market profile: Agriculture*. https://www.ilo.org

Ismail, B. I., Sehmi, M. N. M., Ahmad, H., Baharom, S. H., & Khalid, M. F. (2023). Robotic research platform for agricultural environment: Unmanned ground vehicle for oil palm plantation. *Journal of Cases on Information Technology, 25*(1). https://doi.org/10.4018/JCIT.321852

Jelsma, I., Woittiez, L. S., Ollivier, J., & Dharmawan, A. H. (2019). Do wealthy farmers implement better agricultural practices? An assessment of implementation of good agricultural practices among different types of independent oil palm smallholders in Riau, Indonesia. *Agricultural Systems*. https://doi.org/10.1016/j.agsy.2018.11.004

Judijanto, L. (2026). Skills development and training pathways for sustainable palm oil employment: A review of competency-based approaches to green job creation. *Annals of Social Sciences & Management Studies, 12*(1). https://doi.org/10.19080/ASM.2026.12.555845

Kour, V., Arora, S., & Singh, A. (2023). Application of AI techniques and robotics in agriculture: A review. *Artificial Intelligence in the Life Sciences, 3*, Article 100057. https://doi.org/10.1016/j.ailsci.2023.100057

Lai, J. W., Ramli, H. R., Ismail, L. I., & Hasan, W. W. Z. (2023). Oil palm fresh fruit bunch ripeness detection methods: A systematic review. *Agriculture, 13*(1), Article 156. https://doi.org/10.3390/agriculture13010156

Lee, S., & Abdullah, M. I. (2024). Antecedents of internal reputation and its consequences on organizational outcomes: A systematic review. *International Journal of Organization Theory & Behavior, 27*(1), 55–79. https://doi.org/10.1108/IJOTB-10-2022-0193

Liang, H., Fan, J., & Wang, Y. (2025). Artificial intelligence, technological innovation, and employment transformation for sustainable development: Evidence from China. *Sustainability*. https://doi.org/10.3390/su17093842

Lowenberg-DeBoer, J., Huang, I. Y., Grigoriadis, V., & Blackmore, S. (2020). Economics of robots and automation in field crop production. *Precision Agriculture, 21*(2), 278–299. https://doi.org/10.1007/s11119-019-09667-5

Moutik, I. (2025). Artificial intelligence as a driver for women's empowerment in agriculture: A theoretical ecosystem for inclusive leadership and sustainable development. *Business Ethics and Leadership, 9*(2), 200–210. https://doi.org/10.61093/bel.9(2).200-210.2025

Mukhlis, M., Daniswara, N., Abdillah, A., & Sofiaturrohmah, S. (2025). The intersectional lens: Unpacking the socio-ecological impacts of oil palm expansion in rural Indonesia. *Sustainability*. https://doi.org/10.3390/su172310570

Osuna-Velarde, D. V., Salazar-Echeagaray, J. E., Bueno-Fernández, M. M., Rosado-Castellanos, D. U., Cañarte-Vélez, C. R., Baque-Cantos, M. A., Baque-Parrales, E. M., Granados-Aya, F. A., Cano-Vargas, Á. A., Cedeño-Ramírez, J. D., Lemos-Tamayo, J., & Rincón-Guio, C. (2024). The confluence of Logistics 4.0 and agribusiness: A systematic review and future directions. *Journal of Infrastructure, Policy and Development, 8*(2), 2871. https://doi.org/10.24294/jipd.v8i2.2871

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372*, n71. https://doi.org/10.1136/bmj.n71

Pareira, S. P. (2023). *Achieving Indonesian palm oil farm-to-table traceability through ISPO-RSPO harmonization*. Centre for Indonesian Policy Studies (CIPS). https://repository.cips-indonesia.org

Rannando, R., Tujannah, M., Azmi, Y., & Sahfitra, A. A. (2025). Economic analysis of the losses of oil palm (*Elaeis guineensis* Jacq.) loose fruits on flat terrain at Agritasari Prima Ltd. *Open Science and Technology*. https://doi.org/10.33292/ost.v5i1.144

Thaddeus, D. J., Bakri, M. A. M., Khalid, M. R. M., Ahmad, M. R., Azaman, M. I. H., Mustaffa, N. K., Radzi, M. K. F. M., & Ramli, A. S. (2023). An overview of the benefits and advantages of implementing mechanisation in the oil palm plantation: A look at fresh fruit bunch (FFB) evacuation. *Advances in Agricultural and Food Research Journal*. https://doi.org/10.36877/aafrj.a0000411

Voutier, P., & Woo, W. (2021). *Digital agriculture in ASEAN: Strategies for donor impact*. Grow Asia. http://exchange.growasia.org

World Economic Forum. (2025). *The future of jobs report 2025*. World Economic Forum. https://www.weforum.org

Yang, M., Kumar, P., Bhola, J., & Shabaz, M. (2021). Development of image recognition software based on artificial intelligence algorithm for the efficient sorting of apple fruit. *Multimedia Tools and Applications, 81*, 4909–4938. https://doi.org/10.1007/s11042-021-11448-6

Yang, S., Zhang, Y., Liao, Z., Ren, Y., Lu, Y., & Qu, H. (2025). Artificial intelligence and urban employment in China's agricultural sector: Conditions for job creation across skill levels. *Journal of Rural Studies, 120*, Article 103845. https://doi.org/10.1016/j.jrurstud.2025.103845

Yu, K., Shi, Y., & Feng, J. (2024). The influence of robot applications on rural labor transfer. *Humanities and Social Sciences Communications, 11*, Article 1045. https://doi.org/10.1057/s41599-024-03201-9