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Artificial Intelligence in the Digital Economy: Increasing Productivity or Threatening the Workforce

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ABSTRACT

This article examines the role of Artificial Intelligence (AI) in the digital economy by focusing on two main questions: whether AI increases productivity or threatens the workforce. The study used a review of the structured literature and secondary data from the WEF, ILO, McKinsey, OECD, APJII, and digital economy reports. The results show that AI has the potential to increase productivity through routine task automation, improved prediction, service personalization, and acceleration of innovation. However, these benefits are not automatic because they depend on data quality, organizational design, worker skills, and ethical governance. Labor threats mainly occur at the level of routine tasks, not solely at the position. The novelty of this article is a three-layer framework of productivity, employment risk, and transitional governance to read the impact of AI in Indonesia. The article recommends human-AI augmentation strategies, task-based reskilling and AI adoption support for MSMEs.

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1. INTRODUCTION

Artificial Intelligence (AI) has become at the core of the discussion of the digital economy as this technology is no longer limited to machine automation, but enters the areas of cognitive work such as writing, data analysis, customer service, design, programming, marketing, and prediction-based decision-making. In the digital economy, AI is present as a recommendation engine, chatbot, fraud detection system, demand analytics, logistics optimization, advertising personalization, and managerial decision support. Therefore, the important question is no longer whether AI will be used, but rather how AI changes productivity, job structure, and skill needs [1]-[7].

The World Economic Forum's 2025 report projects that structural changes in the workforce until 2030 could create 170 million new jobs and shift 92 million jobs, resulting in a net increase of 78 million jobs. However, the same report emphasizes that the skills gap is the biggest obstacle to business transformation, with nearly 40% of job skills estimated to change [1]. Meanwhile, the ILO developed an occupational exposure index to task-based generative AI, which suggests that the impact of AI needs to be seen at the level of work activity, not just the name of the job title [2]. Previous research provides a solid foundation but also shows uncertainty. Autor explains that technology often replaces certain tasks, but at the same time creates new demands through human-machine complementarity [8]. Brynjolfsson and McAfee emphasize that the digital wave can increase productivity, but the benefits depend on organization and skills [9]. Frey and Osborne estimate the risks of computerization in many jobs, especially routine ones [10]. Acemoglu and Restrepo caution that automation can reduce wages and employment if it is not balanced by the creation of new tasks [11]. Agrawal et al. view AI as a predictive technology that lowers the cost of decision-making and changes the value of human skills [12].

In Indonesia, the AI debate needs to be linked to the structure of the digital economy that is still evolving. High internet penetration and ever-increasing GMV of the digital economy open up opportunities for AI adoption in e-commerce, digital payments, financial services, education, healthcare, transportation, and digital governance [6], [7]. However, the level of organizational readiness, data quality, computing infrastructure, data use ethics, and workforce readiness is not evenly distributed. Without proper policy design, AI can magnify the disparity between large companies that have data and technology capital and MSMEs that are still struggling with basic digital literacy. AI can increase productivity through four channels. First, AI reduces the time of routine tasks such as compiling reports, classifying customer tickets, or searching for information. Second, AI improves the quality of predictions, such as demand prediction, credit risk, and transaction anomaly detection. Third, AI enables personalization of services at scale. Fourth, AI supports product innovation through simulation, design, and experimentation faster. However, productivity does not automatically arise because organizations must reorganize work processes, build data governance, train employees, and set accountability boundaries between humans and systems [13]-[16]. On the labor side, the impact of AI is twofold. Jobs that contain repetitive and easily standardized tasks are more susceptible to being replaced or reduced. In contrast, jobs that require complex assessment, empathy, creativity, coordination, leadership, and understanding of local contexts are more likely to be amplified by AI. As such, the question of productivity versus the threat of labor is too narrow to be read as a binary choice. A more precise analysis is to differentiate between automation, augmentation, and task transformation.

The novelty of this article lies in the preparation of a three-layer framework to assess AI in Indonesia's digital economy: the productivity layer, the employment risk layer, and the transition governance layer. This framework places AI not as a neutral technology that automatically brings benefits, but as a socio-technical system whose outcomes are determined by organizational strategy, institutional quality, and skill investment. With this framework, the article answers in a more balanced way whether AI increases productivity or threatens the workforce.

2. METHOD

The research method used was a structured literature study with secondary data analysis. Key quantitative data came from the WEF, ILO, McKinsey, OECD, e-Conomy SEA report, and APJII. The academic literature was selected to represent three traditions: automation and task theory, the economics of digital productivity, and AI skills governance and ethics [1]-[25]. The analysis was carried out using a task-based exposure framework. This framework assesses work as a collection of tasks. Each task can have a different relationship with AI: replaced, accelerated, improved in quality, or still requires humans. With such an approach, the article avoids the generalization that one job will be completely lost or completely safe. In addition, productivity mapping is carried out through indicators of potential economic value, productivity estimation, and projected job changes. The research stages include tracing sources, extracting indicators, classifying findings, compiling visualizations, and synthesizing policies. Visualizations are made from numbers explicitly reported by authoritative sources. The limitation of the study is that it has not used micro data of Indonesian companies, so the results are conceptual and macro-descriptive.

Table 1. Classification of AI impact by task type

Task type	Relationship with AI	Impact on workers	Policy response
Administrative Procedure	High Automation	Reduced working time and role changes	Operational reskilling and task transition
Analytical-iterative	Augmentasi	faster output but needs validation	Training prompts, data literacy, audits
Interpersonal	Complement	AI supports information, humans maintain empathy	Service standards and ethics
Strategic-creative	Selective augmentation	Faster Ideas, Decisions Are Still Human	Leadership and accountability
Risk monitoring	human-in-the-loop	Anomaly detection is improved	Regulation, Documentation, Audit Bias

3. RESULTS AND DISCUSSION

3.1. AI as a Productivity Engine

The results of the synthesis show that AI has the potential to increase productivity through time savings, improved prediction accuracy, personalization of services, and expansion of innovation capacity. McKinsey estimates that generative AI can increase labor productivity by 0.1 to 0.6 percentage points per year through 2040, while the combined automation of all technologies can add 0.5 to 3.4 percentage points per year if the freed up working time can be productively reallocating [3]. This means that the benefits of AI depend on the organization's ability to reorganize work processes, rather than just buying AI software. In Indonesia's digital economy, the productivity potential is most quickly seen in activities that have been digitized, such as marketplace customer service, transaction verification, stock management, digital loan risk assessment, customer segmentation, and marketing content. However, increasing productivity requires clean data, clear SOPs, human supervision, and performance measurement that not only calculates cost efficiency, but also service quality and data security.

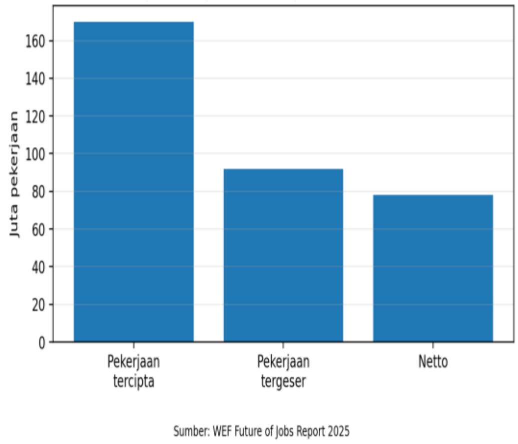

Figure 2. Projected jobs created, shifted, and net until 2030.

3.2. Workforce Threat: Task Automation, Not Just Job Loss

The threat of AI to the workforce mainly arises in tasks that are repetitive, rules-based, and have standardized outputs. Examples are data entry, routine document processing, first-rate customer responses, simple content creation, and administrative information retrieval. However, jobs rarely consist of a single task. Many jobs have a combination of routine and non-routine tasks. Therefore, AI more often changes the content of the job before removing the job completely [8], [11], [14], [15]. The biggest risk for workers is not just job loss, but a decline in the value of old skills. Workers who were previously superior in being able to do administrative tasks quickly can lose the edge if the task is automated. In contrast, workers who are able to formulate problems, examine AI outputs, communicate across functions, and make ethical decisions can gain added value. As such, AI threats should be answered with task-specific reskilling rather than overly superficial general training.

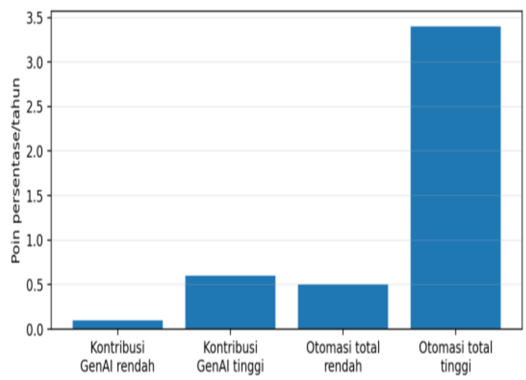

Figure 3. Estimating the contribution of AI and automation to annual productivity growth.

3.3. Skills Gap and Risk of Inequality

The WEF affirms that the skills gap is a major obstacle to transformation. If large companies are able to invest in AI, data engineers, and in-house training, while MSMEs are not, then digital productivity can be concentrated on large actors. Inequality can also arise between workers who have data literacy and workers who do not. The OECD shows that AI is likely to increase the need for highly educated workers and digital skills, while human skills such as creativity, problem solving, communication, and leadership remain important [5]. In Indonesia, this issue is important because the digital economy relies heavily on MSMEs and informal workers. Too fast adoption of AI without training can create new pressures, for example higher job targets, algorithmic supervision, or more flexible but less secure employment contracts. Therefore, AI governance should include worker protection and training access as part of a productivity strategy.

3.4. Policy Framework: From Automation to Augmentation

The augmented reality framework puts AI as a co-pilot, not a total replacement for humans. In this model, AI handles the tasks of searching, drafting, summarizing, classification, or pattern detection, while humans are responsible for validation, interpretation, final decisions, empathy, and accountability. This model is better suited for digital economies that require public trust, such as financial services, healthcare, education, and government administration. The policies required include standards for transparency in the use of AI, bias audits, data protection, skills certification, training incentives, and AI adoption support for MSMEs. Governments and universities can play a role as providers of AI literacy, not just as technology users. The business world needs to assess the success of AI through responsible productivity indicators: work time saved, quality of service, decision accuracy, customer satisfaction, and worker well-being.

3.5. Relevance of Results to Relevant Research

The findings of this article are consistent with Autor who rejects the view that automation always removes the entire job because technology also creates new tasks [8]. However, this article is also in line with Acemoglu and Restrepo who warn that automation can be detrimental to workers if the creation of new tasks is slow [11]. McKinsey's estimates of productivity potential support the argument that AI can be a source of growth, but the WEF and OECD findings suggest that such benefits require reskilling and organizational change [1], [3], [5]. As such, AI is not an automatic answer to productivity, but rather an opportunity to be managed. In the Indonesian context, this article expands the literature by placing AI in the structure of the digital economy that still faces a digital capability gap. The results of the synthesis show that the safest strategy is not to reject AI, but to direct AI to augmentation, competency enhancement, and fair governance.

Table 2. AI opportunity-risk matrix in Indonesia's digital economy

Level of analysis	Opportunities	Risks	Monitoring indicators
Company	Process efficiency, 24/7 service	Data bias, failed investments	ROI, accuracy, customer satisfaction
Employees	Faster tasks, premium skills	displacement, deskilling	Access to training, work mobility
MSMEs	Cheap content and analytics	Platform dependencies	Productive AI adoption
Regulator	More efficient public services	Privacy and accountability	audit, security, reporting
Education	kurikulum AI literacy	Access gap	Certification and Competency Achievement

3.7. Practical Implications and Critical Reflection

The implication for organizations is the need for a task map before adopting AI. Many organizations buy AI applications without knowing which processes need improvement the most. Task mapping helps determine whether AI will be used for automation, augmentation, prediction, or risk monitoring. Without such mapping, AI investments risk becoming expensive experiments that don't produce measurable value. Employees also need a change in the way they learn. AI skills not only mean being able to use a single application, but being able to formulate questions, validate answers, understand the limitations of the model, maintain data confidentiality, and combine AI output with professional judgment. In other words, AI literacy is critical thinking literacy in a technological environment.

For MSMEs, AI can be a low-cost tool for creating product descriptions, promotional designs, stock planning, and customer analysis. However, MSMEs need to be guided not to enter sensitive data into insecure systems and not to accept AI output without verification. Practical mentoring is needed more than too generic conceptual seminars. From an employment perspective, social dialogue needs to be strengthened. The use of AI in the workplace should be discussed transparently, especially if it affects productivity targets, supervision, or role changes. Employees need to know when AI is used, what data is processed, and how AI results affect performance appraisals. Governments can foster an inclusive AI ecosystem through training incentives, ethics guidance, audit standardization, and support for vocational education. Without inclusive policies, the benefits of AI can be concentrated in large companies and highly educated workers, while vulnerable workers are only subjected to automation pressures.

3.8. Advanced Analysis: Scenarios, Indicators, and Implementation Strategies

The high growth scenario of AI adoption in the digital economy illustrates the conditions when digital infrastructure, user trust, and business readiness grow simultaneously. In this scenario, the actors involved include workers, managers, platform companies, MSMEs, universities, technology providers, and governments. The key issue is the shift from job automation to task redesign so that AI strengthens the speed, prediction quality, and creativity of humans. In order for the benefits not to stop at increasing adoption rates, the analysis needs to pay attention to the quality of the process, the distribution of benefits, and the ability of users to understand the consequences of digital decisions. Risks to anticipate include routine task displacement, deskilling, algorithmic bias, data leakage, over-supervision, and skills access inequality.

Therefore, relevant strategies are task-based reskilling, AI auditing, data governance, human-in-the-loop, and AI adoption incentives for MSMEs. Indicators that can be monitored include work time saved, output productivity, error rate, training access, worker mobility, and user satisfaction. This approach helps research move from trend descriptions to more responsible impact evaluation.

The uneven growth scenario in AI adoption in the digital economy illustrates conditions when adoption is concentrated in urban areas, large enterprises, or higher-educated users. In this scenario, the actors involved include workers, managers, platform companies, MSMEs, universities, technology providers, and governments. The key issue is the shift from job automation to task redesign so that AI strengthens the speed, prediction quality, and creativity of humans. In order for the benefits not to stop at increasing adoption rates, the analysis needs to pay attention to the quality of the process, the distribution of benefits, and the ability of users to understand the consequences of digital decisions. Risks to anticipate include routine task displacement, deskilling, algorithmic bias, data leakage, over-supervision, and skills access inequality. Therefore, relevant strategies are task-based reskilling, AI auditing, data governance, human-in-the-loop, and AI adoption incentives for MSMEs. Indicators that can be monitored include work time saved, output productivity, error rate, training access, worker mobility, and user satisfaction. This approach helps research move from trend descriptions to more responsible impact evaluation. The consumer protection scenario of AI adoption in the digital economy illustrates the conditions when technological innovation is accompanied by complaint mechanisms, security standards, and information transparency. In this scenario, the actors involved include workers, managers, platform companies, MSMEs, universities, technology providers, and governments. The key issue is the shift from job automation to task redesign so that AI strengthens the speed, prediction quality, and creativity of humans. In order for the benefits not to stop at increasing adoption rates, the analysis needs to pay attention to the quality of the process, the distribution of benefits, and the ability of users to understand the consequences of digital decisions. Risks to anticipate include routine task displacement, deskilling, algorithmic bias, data leakage, over-supervision, and skills access inequality. Therefore, relevant strategies are task-based reskilling, AI auditing, data governance, human-in-the-loop, and AI adoption incentives for MSMEs. Indicators that can be monitored include work time saved, output productivity, error rate, training access, worker mobility, and user satisfaction. This approach helps research move from trend descriptions to more responsible impact evaluation.

The cost efficiency scenario in AI adoption in the digital economy describes the conditions when business actors use technology to reduce operational costs without reducing service quality. In this scenario, the actors involved include workers, managers, platform companies, MSMEs, universities, technology providers, and governments. The key issue is the shift from job automation to task redesign so that AI strengthens the speed, prediction quality, and creativity of humans. In order for the benefits not to stop at increasing adoption rates, the analysis needs to pay attention to the quality of the process, the distribution of benefits, and the ability of users to understand the consequences of digital decisions. Risks to anticipate include routine task displacement, deskilling, algorithmic bias, data leakage, over-supervision, and skills access inequality. Therefore, relevant strategies are task-based reskilling, AI auditing, data governance, human-in-the-loop, and AI adoption incentives for MSMEs. Indicators that can be monitored include work time saved, output productivity, error rate, training access, worker mobility, and user satisfaction. This approach helps research move from trend descriptions to more responsible impact evaluation.

The scenario of platform dependence on AI adoption in the digital economy illustrates a condition when small actors are overly dependent on the rules, costs, and algorithms of large digital actors. In this scenario, the actors involved include workers, managers, platform companies, MSMEs, universities, technology providers, and governments. The key issue is the shift from job automation to task redesign so that AI strengthens the speed, prediction quality, and creativity of humans. In order for the benefits not to stop at increasing adoption rates, the analysis needs to pay attention to the quality of the process, the distribution of benefits, and the ability of users to understand the consequences of digital decisions. Risks to anticipate include routine task displacement, deskilling, algorithmic bias, data leakage, over-supervision, and skills access inequality. Therefore, relevant strategies are task-based reskilling, AI auditing, data governance, human-in-the-loop, and AI adoption incentives for MSMEs. Indicators that can be monitored include work time saved, output productivity, error rate, training access, worker mobility, and user satisfaction. This approach helps research move from trend descriptions to more responsible impact evaluation.

The low literacy scenario on AI adoption in the digital economy describes the conditions when users adopt technology due to promotion, but do not yet understand its risks, rights, and obligations. In this scenario, the actors involved include workers, managers, platform companies, MSMEs, universities, technology providers, and governments. The key issue is the shift from job automation to task redesign so that AI strengthens the speed, prediction quality, and creativity of humans. In order for the benefits not to stop at increasing adoption rates, the analysis needs to pay attention to the quality of the process, the distribution of benefits, and the ability of users to understand the consequences of digital decisions. Risks to anticipate include routine task displacement, deskilling, algorithmic bias, data leakage, over-supervision, and skills access inequality. Therefore, relevant strategies are task-based reskilling, AI auditing, data governance, human-in-the-loop, and AI adoption incentives for MSMEs. Indicators that can be monitored include work time saved, output productivity, error rate, training access, worker mobility, and user satisfaction. This approach helps research move from trend descriptions to more responsible impact evaluation.

The data governance scenario in AI adoption in the digital economy describes the conditions when transaction and behavioral data become an economic asset as well as a source of privacy risk. In this scenario, the actors involved include workers, managers, platform companies, MSMEs, universities, technology providers, and governments. The key issue is the shift from job automation to task redesign so that AI strengthens the speed, prediction quality, and creativity of humans. In order for the benefits not to stop at increasing adoption rates, the analysis needs to pay attention to the quality of the process, the distribution of benefits, and the ability of users to understand the consequences of digital decisions. Risks to anticipate include routine task displacement, deskilling, algorithmic bias, data leakage, over-supervision, and skills access inequality. Therefore, relevant strategies are task-based reskilling, AI auditing, data governance, human-in-the-loop, and AI adoption incentives for MSMEs. Indicators that can be monitored include work time saved, output productivity, error rate, training access, worker mobility, and user satisfaction. This approach helps research move from trend descriptions to more responsible impact evaluation.

The MSME inclusion scenario in the adoption of AI in the digital economy illustrates the conditions when technology opens up market access, recording, payment, and financing for small businesses. In this scenario, the actors involved include workers, managers, platform companies, MSMEs, universities, technology providers, and governments. The key issue is the shift from job automation to task redesign so that AI strengthens the speed, prediction quality, and creativity of humans. In order for the benefits not to stop at increasing adoption rates, the analysis needs to pay attention to the quality of the process, the distribution of benefits, and the ability of users to understand the consequences of digital decisions. Risks to anticipate include routine task displacement, deskilling, algorithmic bias, data leakage, over-supervision, and skills access inequality. Therefore, relevant strategies are task-based reskilling, AI auditing, data governance, human-in-the-loop, and AI adoption incentives for MSMEs. Indicators that can be monitored include work time saved, output productivity, error rate, training access, worker mobility, and user satisfaction. This approach helps research move from trend descriptions to more responsible impact evaluation.

The adaptive regulatory scenario on AI adoption in the digital economy describes a situation when governments make clear rules but still provide room for experimentation for innovation. In this scenario, the actors involved include workers, managers, platform companies, MSMEs, universities, technology providers, and governments. The key issue is the shift from job automation to task redesign so that AI strengthens the speed, prediction quality, and creativity of humans. In order for the benefits not to stop at increasing adoption rates, the analysis needs to pay attention to the quality of the process, the distribution of benefits, and the ability of users to understand the consequences of digital decisions. Risks to anticipate include routine task displacement, deskilling, algorithmic bias, data leakage, over-supervision, and skills access inequality. Therefore, relevant strategies are task-based reskilling, AI auditing, data governance, human-in-the-loop, and AI adoption incentives for MSMEs. Indicators that can be monitored include work time saved, output productivity, error rate, training access, worker mobility, and user satisfaction. This approach helps research move from trend descriptions to more responsible impact evaluation.

The system resilience scenario in AI adoption in the digital economy describes the conditions when the ecosystem is able to stay running in the event of network disruptions, market changes, or security risks. In this scenario, the actors involved include workers, managers, platform companies, MSMEs, universities, technology providers, and governments. The key issue is the shift from job automation to task redesign so that AI strengthens the speed, prediction quality, and creativity of humans. In order for the benefits not to stop at increasing adoption rates, the analysis needs to pay attention to the quality of the process, the distribution of benefits, and the ability of users to understand the consequences of digital decisions. Risks to anticipate include routine task displacement, deskilling, algorithmic bias, data leakage, over-supervision, and skills access inequality. Therefore, relevant strategies are task-based reskilling, AI auditing, data governance, human-in-the-loop, and AI adoption incentives for MSMEs. Indicators that can be monitored include work time saved, output productivity, error rate, training access, worker mobility, and user satisfaction. This approach helps research move from trend descriptions to more responsible impact evaluation.

The educational collaboration scenario on AI adoption in the digital economy describes the conditions when colleges, industry, and government provide curricula that are relevant to digital needs. In this scenario, the actors involved include workers, managers, platform companies, MSMEs, universities, technology providers, and governments. The key issue is the shift from job automation to task redesign so that AI strengthens the speed, prediction quality, and creativity of humans. In order for the benefits not to stop at increasing adoption rates, the analysis needs to pay attention to the quality of the process, the distribution of benefits, and the ability of users to understand the consequences of digital decisions. Risks to anticipate include routine task displacement, deskilling, algorithmic bias, data leakage, over-supervision, and skills access inequality. Therefore, relevant strategies are task-based reskilling, AI auditing, data governance, human-in-the-loop, and AI adoption incentives for MSMEs. Indicators that can be monitored include work time saved, output productivity, error rate, training access, worker mobility, and user satisfaction. This approach helps research move from trend descriptions to more responsible impact evaluation. The ethical and accountability scenarios on AI adoption in the digital economy describe the conditions when technology-based decisions can be explained, audited, and accounted for. In this scenario, the actors involved include workers, managers, platform companies, MSMEs, universities, technology providers, and governments. The key issue is the shift from job automation to task redesign so that AI strengthens the speed, prediction quality, and creativity of humans. In order for the benefits not to stop at increasing adoption rates, the analysis needs to pay attention to the quality of the process, the distribution of benefits, and the ability of users to understand the consequences of digital decisions. Risks to anticipate include routine task displacement, deskilling, algorithmic bias, data leakage, over-supervision, and skills access inequality. Therefore, relevant strategies are task-based reskilling, AI auditing, data governance, human-in-the-loop, and AI adoption incentives for MSMEs. Indicators that can be monitored include work time saved, output productivity, error rate, training access, worker mobility, and user satisfaction. This approach helps research move from trend descriptions to more responsible impact evaluation. The regional competitiveness scenario on the adoption of AI in the digital economy describes the conditions when regions are not only users, but also producers of value in the digital economy. In this scenario, the actors involved include workers, managers, platform companies, MSMEs, universities, technology providers, and governments. The key issue is the shift from job automation to task redesign so that AI strengthens the speed, prediction quality, and creativity of humans. In order for the benefits not to stop at increasing adoption rates, the analysis needs to pay attention to the quality of the process, the distribution of benefits, and the ability of users to understand the consequences of digital decisions. Risks to anticipate include routine task displacement, deskilling, algorithmic bias, data leakage, over-supervision, and skills access inequality. Therefore, relevant strategies are task-based reskilling, AI auditing, data governance, human-in-the-loop, and AI adoption incentives for MSMEs. Indicators that can be monitored include work time saved, output productivity, error rate, training access, worker mobility, and user satisfaction. This approach helps research move from trend descriptions to more responsible impact evaluation.

The channel integration scenario in AI adoption in the digital economy describes a condition when physical and digital channels complement each other in a single user journey. In this scenario, the actors involved include workers, managers, platform companies, MSMEs, universities, technology providers, and governments. The key issue is the shift from job automation to task redesign so that AI strengthens the speed, prediction quality, and creativity of humans. In order for the benefits not to stop at increasing adoption rates, the analysis needs to pay attention to the quality of the process, the distribution of benefits, and the ability of users to understand the consequences of digital decisions. Risks to anticipate include routine task displacement, deskilling, algorithmic bias, data leakage, over-supervision, and skills access inequality. Therefore, relevant strategies are task-based reskilling, AI auditing, data governance, human-in-the-loop, and AI adoption incentives for MSMEs. Indicators that can be monitored include work time saved, output productivity, error rate, training access, worker mobility, and user satisfaction. This approach helps research move from trend descriptions to more responsible impact evaluation.

The continuous learning scenario on AI adoption in the digital economy describes the conditions when users and business actors continue to adjust behaviors based on experience and data. In this scenario, the actors involved include workers, managers, platform companies, MSMEs, universities, technology providers, and governments. The key issue is the shift from job automation to task redesign so that AI strengthens the speed, prediction quality, and creativity of humans. In order for the benefits not to stop at increasing adoption rates, the analysis needs to pay attention to the quality of the process, the distribution of benefits, and the ability of users to understand the consequences of digital decisions. Risks to anticipate include routine task displacement, deskilling, algorithmic bias, data leakage, over-supervision, and skills access inequality. 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In order for the benefits not to stop at increasing adoption rates, the analysis needs to pay attention to the quality of the process, the distribution of benefits, and the ability of users to understand the consequences of digital decisions. Risks to anticipate include routine task displacement, deskilling, algorithmic bias, data leakage, over-supervision, and skills access inequality. Therefore, relevant strategies are task-based reskilling, AI auditing, data governance, human-in-the-loop, and AI adoption incentives for MSMEs. Indicators that can be monitored include work time saved, output productivity, error rate, training access, worker mobility, and user satisfaction. This approach helps research move from trend descriptions to more responsible impact evaluation. The impact measurement scenario on AI adoption in the digital economy describes a condition when success is not only calculated from transaction volume, but also the quality of socio-economic benefits. In this scenario, the actors involved include workers, managers, platform companies, MSMEs, universities, technology providers, and governments. The key issue is the shift from job automation to task redesign so that AI strengthens the speed, prediction quality, and creativity of humans. In order for the benefits not to stop at increasing adoption rates, the analysis needs to pay attention to the quality of the process, the distribution of benefits, and the ability of users to understand the consequences of digital decisions. Risks to anticipate include routine task displacement, deskilling, algorithmic bias, data leakage, over-supervision, and skills access inequality. Therefore, relevant strategies are task-based reskilling, AI auditing, data governance, human-in-the-loop, and AI adoption incentives for MSMEs. Indicators that can be monitored include work time saved, output productivity, error rate, training access, worker mobility, and user satisfaction. This approach helps research move from trend descriptions to more responsible impact evaluation. The sustainability scenario on AI adoption in the digital economy illustrates the conditions when digital growth considers worker welfare, consumer protection, and resource efficiency. In this scenario, the actors involved include workers, managers, platform companies, MSMEs, universities, technology providers, and governments. The key issue is the shift from job automation to task redesign so that AI strengthens the speed, prediction quality, and creativity of humans. In order for the benefits not to stop at increasing adoption rates, the analysis needs to pay attention to the quality of the process, the distribution of benefits, and the ability of users to understand the consequences of digital decisions. Risks to anticipate include routine task displacement, deskilling, algorithmic bias, data leakage, over-supervision, and skills access inequality. Therefore, relevant strategies are task-based reskilling, AI auditing, data governance, human-in-the-loop, and AI adoption incentives for MSMEs. Indicators that can be monitored include work time saved, output productivity, error rate, training access, worker mobility, and user satisfaction. This approach helps research move from trend descriptions to more responsible impact evaluation.

3.9. Findings Operationalization Matrix

Table 3. Operationalization of advanced analytics dimensions

Dimensions	Operational definition	Indicator	Measurement source
Adoption	How far the technology is used by the target actor	Number of active users, intensity of use, variety of features utilized	User surveys, platform aggregate data, regulator reports
Trust	a level of confidence that the system is safe, fair, and reliable	Complaint Rate, Successful Dispute Resolution, Perception of Security	Perception surveys, complaint data, service audits
Efficiency	Changes in time costs, transaction fees, and administrative fees	Turnaround time, service fee, productivity per transaction	Process observations, operational reports, case studies
Inclusions	the ability of small or vulnerable groups to benefit	participation of MSMEs, rural areas, new users, access to financing	administrative data, MSME surveys, regional mapping
Risks	possible financial, data, reputational, or social loss	cases of fraud, data leakage, misdecisions, user churn	Incident reports, security data, actor interviews
Justice	Distribution of costs and benefits between actors	Margin changes, training access, compliance costs, bargaining positions	Policy analysis, business actor surveys, price data
Sustainability	the ability of the system to survive without harming small actors	User retention, business health, service stability, regulatory adaptation	Data panel, longitudinal studies, program evaluation

3.10. Policy Agenda and Applied Research

The agenda for the Government is to provide adaptive regulations, public data, user protection guidelines, and a safe innovation test room. In the context of AI adoption in the digital economy, this role cannot be carried out in isolation because the digital economy is an ecosystem. The success of one actor depends heavily on the readiness of other actors. For example, industrial innovation requires regulatory certainty, while good regulation requires empirical data and feedback from users. Therefore, collaboration between institutions is a prerequisite for digital transformation to produce broad and accountable benefits. The agenda for universities is to develop a digital economy curriculum, data laboratories, policy-based research, and service to MSMEs. In the context of AI adoption in the digital economy, this role cannot be carried out in isolation because the digital economy is an ecosystem. The success of one actor depends heavily on the readiness of other actors. For example, industrial innovation requires regulatory certainty, while good regulation requires empirical data and feedback from users. Therefore, collaboration between institutions is a prerequisite for digital transformation to produce broad and accountable benefits.

The agenda for the industry is to increase service transparency, user-friendly design, risk audits, and partner capacity building programs. In the context of AI adoption in the digital economy, this role cannot be carried out in isolation because the digital economy is an ecosystem. The success of one actor depends heavily on the readiness of other actors. For example, industrial innovation requires regulatory certainty, while good regulation requires empirical data and feedback from users. Therefore, collaboration between institutions is a prerequisite for digital transformation to produce broad and accountable benefits. The agenda for MSMEs is to build a digital identity, record transactions, reputation management, and product differentiation strategies. In the context of AI adoption in the digital economy, this role cannot be carried out in isolation because the digital economy is an ecosystem. The success of one actor depends heavily on the readiness of other actors. For example, industrial innovation requires regulatory certainty, while good regulation requires empirical data and feedback from users. Therefore, collaboration between institutions is a prerequisite for digital transformation to produce broad and accountable benefits. The agenda for consumers is to improve risk literacy, the ability to check information, and the discipline in making digital decisions. In the context of AI adoption in the digital economy, this role cannot be carried out in isolation because the digital economy is an ecosystem. The success of one actor depends heavily on the readiness of other actors. For example, industrial innovation requires regulatory certainty, while good regulation requires empirical data and feedback from users. Therefore, collaboration between institutions is a prerequisite for digital transformation to produce broad and accountable benefits.

The agenda for local communities is to bridge the needs of the community with digital solutions that are in accordance with the language, culture, and character of the region. In the context of AI adoption in the digital economy, this role cannot be carried out in isolation because the digital economy is an ecosystem. The success of one actor depends heavily on the readiness of other actors. For example, industrial innovation requires regulatory certainty, while good regulation requires empirical data and feedback from users. Therefore, collaboration between institutions is a prerequisite for digital transformation to produce broad and accountable benefits. The agenda for technical regulators is to develop standards for interoperability, security, reporting, and audit mechanisms that do not burden small actors. In the context of AI adoption in the digital economy, this role cannot be carried out in isolation because the digital economy is an ecosystem. The success of one actor depends heavily on the readiness of other actors. For example, industrial innovation requires regulatory certainty, while good regulation requires empirical data and feedback from users. Therefore, collaboration between institutions is a prerequisite for digital transformation to produce broad and accountable benefits.

Table 4. Collaborative agenda based on ecosystem actors

Actors	Strategic role	Forms of intervention	Expected output
Government	Provide adaptive regulation, public data, user protection guidelines, and a secure innovation test room	programs, regulations, training, audits, or mentoring	An ecosystem that is more inclusive, safe, and productive
Colleges	developing digital economy curriculum, data laboratories, policy-based research, and service to MSMEs	programs, regulations, training, audits, or mentoring	An ecosystem that is more inclusive, safe, and productive
Industry	Improved service transparency, user-friendly design, risk audits, and partner capacity building programs	programs, regulations, training, audits, or mentoring	An ecosystem that is more inclusive, safe, and productive
MSMEs	Build digital identity, transaction logging, reputation management, and product differentiation strategies	programs, regulations, training, audits, or mentoring	An ecosystem that is more inclusive, safe, and productive
Consumers	Improve risk literacy, information checking ability, and discipline in digital decision-making	programs, regulations, training, audits, or mentoring	An ecosystem that is more inclusive, safe, and productive
Local communities	Bridging the needs of the community with digital solutions that are appropriate to the language, culture, and character of the region	programs, regulations, training, audits, or mentoring	An ecosystem that is more inclusive, safe, and productive
Technical regulator	Develop standards for interoperability, security, reporting, and audit mechanisms that do not burden small actors	programs, regulations, training, audits, or mentoring	An ecosystem that is more inclusive, safe, and productive

3.11. Limitations of Analysis and Anticipation of Bias

The first limitation is the use of aggregate data. Aggregate data is useful for seeing the scale and direction of change, but it is not yet able to explain variations in individual behavior. Differences in income, education, region, age, and digital experience can result in patterns that differ from the national average. Therefore, the results of this article need to be read as a macro synthesis that requires microtesting. The second limitation is the potential for bias in industry report sources. Industry reports often have rich data, but they can also carry certain narrative interests. To reduce bias, this article combines industry reports with government data, regulatory publications, and academic literature. This triangulation does not eliminate all bias, but reinforces the prudence of interpretation. The third limitation is the dynamics of the digital economy which is very fast. User numbers, transactions, regulations, and technology can change in a short period of time. Therefore, this kind of article needs to be updated regularly. Claims that are quantitative should always be accompanied by data years, sources, and interpretation limitations.

The fourth limitation has to do with the concept of success. Many digital analytics focus too much on the number of users or the value of transactions. In fact, more substantive successes include service quality, security, equitable distribution of benefits, strengthening small actors, and consumer protection. This article attempts to expand on the indicator, but its measurement still requires further research. The fifth limitation is the absence of causal modeling. The relationship between technology and behavioral change is not always one-way. Technology influences behavior, but people's behavior also shapes technological features. Follow-up studies can use panel models, field experiments, or mixed methods to test the mechanism more robustly.

Table 5. Potential bias and analysis mitigation strategies

Potential bias	Impact on interpretation	How to mitigate
Aggregate data	hide individual and regional variations	Use microsurveys and spatial analysis
Industry reports	narrative can be overly optimistic	Triangulation with regulatory and academic data
Quick changes	numbers can become obsolete	Enter the year and update the data
Focus volume	Ignoring the quality of the benefits	Add safety, inclusion, and satisfaction indicators
Without causality	The relationship is only descriptive	Continue with empirical models and mixed methods

3.12. Integrative Narrative for Research Model Development

Advanced research models can be built by placing individual, organizational, and institutional factors as interacting variables. Individual factors include literacy, experience, risk perception, and trust. Organizational factors include technology capacity, service quality, and data management capabilities. Institutional factors include regulations, public infrastructure, and social norms. With this structure, the analysis does not stop at the simple relationship between technology and behavior, but looks at how technology works through a specific socio-economic environment.

Quantitative approaches can use structural equation models to test the relationship between convenience, usability, trust, risk, and intent of use. However, the model needs to be equipped with Indonesian contextual variables, such as community strength, promotional role, family influence, fraud experience, and the quality of regional infrastructure. Without contextual variables, digital adoption models tend to be too general and lack a grasp of the diversity of people's behaviors. A qualitative approach remains important because many digital decisions are influenced by reasons that are not always reflected in numbers. In-depth interviews can delve into how businesses understand the benefits and risks, how consumers interpret security, and how regulators see the line between innovation and protection. Narrative data like this is useful to explain why two groups with the same access to technology might exhibit different behaviors. The blended method is a strong choice for this topic. Surveys can provide an overview of general patterns, while interviews and case studies can shed light on the mechanisms behind those patterns. For example, survey data can show that trust influences adoption, but interviews can shed light on the source of that trust: personal experiences, family recommendations, platform reputation, or previous problem-solving success.

Spatial analysis is also relevant because Indonesia's digital economy is unevenly distributed between regions. Regions with strong internet infrastructure, high merchant density, and good digital literacy will experience faster transformation. In contrast, regions with limited access may experience slower adoption or use only basic features. Therefore, regional maps, digital readiness indices, and local transaction data can enrich subsequent research. Policy evaluations should look not only at administrative outputs, but also at the real impact on users. Digitalization programs often succeed in increasing the number of accounts, merchants, or transactions, but not necessarily in increasing profits, well-being, or security. Impact evaluation needs to distinguish between outputs, outcomes, and impacts. Output is the number of participants or transactions; Outcome is a change in ability; Impact is a change in well-being and sustainability.

In the development of theory, the Indonesian context can contribute to the global digital economy literature because it has a combination of large markets, high internet penetration, dominant MSMEs, archipelago areas, and social diversity. This combination makes Indonesia an important laboratory for understanding how digital technology operates in heterogeneous developing countries. Indonesia's findings can expand theories that have been based on developed countries. In practical terms, advanced research needs to produce instruments that are easy for policymakers to use. Readiness indices, risk dashboards, literacy matrices, and simple audit guidelines can help public institutions and business actors make decisions. Academic articles would be more useful if they could be translated into work tools that improve policies and practices in the field. The development of indicators must pay attention to the balance between efficiency and fairness. Efficiency indicators such as transaction volume, processing time, and service costs need to be paired with fairness indicators such as small group access, cost burden, risk of loss, and ability to file complaints. This balance prevents digital transformation from being judged only by growth, when the quality of growth is just as important.

Finally, the entire analysis needs to keep in mind that technology is a tool, not an end. The main goals of the digital economy are to improve welfare, expand opportunities, strengthen competitiveness, and improve service quality. As technology begins to create new risks, research and policy must be able to correct course. Thus, digital transformation can be a humane, inclusive, and sustainable process.

3.13. Stage-Based Implementation Recommendations

The first stage is needs mapping. Each actor needs to understand the problem they want to solve before choosing a digital solution. This mapping includes the slowest processes, the most frequent emerging risks, the most vulnerable user groups, and available data sources. Without mapping, digital transformation can turn into the use of directionless technology. The second stage is the preparation of minimum standards. Minimum standards are necessary so that innovation does not come at the expense of safety, fairness, and affordability. These standards can be in the form of verification procedures, information quality, limits of responsibility, data protection, and complaint mechanisms. Minimum standards don't have to be complicated, but they should be clear and easy to understand. The third stage is the training of key actors. Training should not only be in the form of one-way socialization, but case-based assistance. Users need to practice dealing with real scenarios such as failed transactions, unclear information, consumer complaints, fraud, regulatory changes, or the use of new features. A practical approach is more effective to improve digital readiness. The fourth phase is a limited pilot project. Before a policy or feature is widely implemented, small-group trials can help identify technical and social issues. Pilot projects can also measure implementation costs, support needs, user responses, and unforeseen risks. The results of the trial should be published concisely so that it can be a joint learning. The fifth stage is data integration and periodic evaluation. The data generated by the digital system must be processed into policy information, not just stored. Periodic evaluations can help see if goals are being achieved, who is benefiting, who is falling behind, and what risks are increasing. This evaluation is the basis for improving regulations and service design. The sixth stage is the strengthening of the correction mechanism. In a digital ecosystem, mistakes can happen very quickly and have a far-reaching impact. Therefore, every policy and service should have an easily accessible remediation path. Users need to know who to report to, how long the response should take, and what evidence is needed. The correction mechanism is an important part of trust. The seventh stage is the development of regional collaboration. Many digital issues emerge locally, such as market trader literacy, network quality, communication language, and transaction habits. Local governments, campuses, communities, and local business actors can be the link between national policies and community needs. Regional collaboration makes digital transformation more grounded. The eighth stage is the preparation of long-term impact indicators. Short-term indicators such as the number of users are important, but not enough. Long-term indicators need to assess increased revenue, business efficiency, user safety, compliance, access to financing, and quality of service. With indicators like this, digital transformation can be evaluated in terms of welfare, not just activities. The ninth stage is adaptive regulatory reform. Digital regulations should not be too slow, but they should also not change too often so as to confuse business actors. Public consultation mechanisms, regulatory sandboxes, and regulatory impact evaluations can help maintain a balance between legal certainty and innovation flexibility. The tenth stage is the formation of a responsible digital culture. This culture includes the habit of checking information, respecting personal data, reporting problems, using technology for productivity, and avoiding manipulative practices. Digital culture is not formed only through applications, but through education, institutional examples, and a secure user experience.

3.14. Academic Implications for the Development of the Digital Economy Curriculum

This topic also has academic implications for the development of the digital economy curriculum. It is not enough for students to understand the definition of technology, but they need to be able to read the relationship between data, behavior, regulation, and business strategy. A good curriculum needs to combine economic theory, statistics, data ethics, information systems, and public policy. Learning can be directed to Indonesian case studies so that students see real complexities. The case of marketplaces, AI, digital taxes, QRIS, MSMEs, and consumer protection can be used as material for data-based discussions. Thus, students learn that digital transformation is not only a problem of application, but also a problem of institutions and behavior.

Analytical skills need to be strengthened through the practice of reading official reports, assessing the validity of sources, making simple visualizations, and drafting policy recommendations. This skill is important because many digital economy decisions are made based on ever-changing data. Students need to be trained to be critical of numbers, not just quote them. The curriculum should also include community-based projects. Students can assist MSMEs, traditional markets, schools, or local communities in understanding digital technology. Projects like this bring together theory and practice and help campuses play a role in an inclusive digital transformation. From the research side, universities can build secondary data repositories and survey instruments that can be used across topics. Standardization of instruments facilitates comparisons between time and between regions. With more consistent data, Indonesia's digital economy research can evolve from descriptive writing to stronger empirical analysis. The final implication is the need for digital research ethics. Researchers should be careful in using transaction data, user data, and platform data. The principles of data minimization, anonymization, consent, and storage security should be part of academic training. Without ethics, digital economy research can pose a risk to the subjects it wants to protect.

4. CONCLUSION

AI in the digital economy has two faces. It can increase productivity through routine task acceleration, prediction improvement, service personalization, and innovation. However, AI can also threaten workers whose tasks are easily standardized if organizations only pursue cost efficiency without transition design. The impact of AI is more accurately read at the task level, not just the position. The best strategy for Indonesia is to encourage human-AI augmentation. Governments, universities, and industry need to expand AI literacy, skills certification, ethical audits, data protection, and implementation support for MSMEs. Sustainable productivity is only achieved if AI enhances human capabilities, not just replaces humans. Further research is suggested using micro data of Indonesian companies to measure the impact of AI on actual productivity. Subsequent studies need to compare AI risks by sector and type of occupation. Experimental research is also needed to assess the effectiveness of AI training for entry-level workers and MSMEs.

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REFERENCES

[1] World Economic Forum, The Future of Jobs Report 2025. Geneva, Switzerland: WEF, 2025.
[2] International Labour Organization, Generative AI and Jobs: A Refined Global Index of Occupational Exposure. Geneva, Switzerland: ILO, 2025.
[3] McKinsey Global Institute, The Economic Potential of Generative AI: The Next Productivity Frontier. New York, NY, USA: McKinsey & Company, 2023.
[4] McKinsey & Company, Superagency in the Workplace: Empowering People to Unlock AI's Full Potential at Work. New York, NY, USA: McKinsey & Company, 2025.
[5] OECD, AI and Skills. Paris, France: OECD Publishing, 2026.
[6] Google, Temasek, and Bain & Company, e-Conomy SEA 2025: From Digital Decade to AI Reality. Singapore: Google, Temasek, Bain & Company, 2025.
[7] Indonesian Internet Service Providers Association, Indonesia Internet Penetration Survey 2024. Jakarta, Indonesia: APJII, 2024.
[8] D. H. Autor, “Why are there still so many jobs? The history and future of workplace automation,” J. Econ. Perspect., vol. 29, no. 3, pp. 3-30, 2015, doi: 10.1257/jep.29.3.3.
[9] E. Brynjolfsson and A. McAfee, The Second Machine Age. New York, NY, USA: W. W. Norton, 2014.
[10] C. B. Frey and M. A. Osborne, “The future of employment: How susceptible are jobs to computerisation?,” Technol. Forecast. Soc. Change, vol. 114, pp. 254-280, 2017, doi: 10.1016/j.techfore.2016.08.019.
[11] D. Acemoglu and P. Restrepo, “Artificial intelligence, automation, and work,” in The Economics of Artificial Intelligence: An Agenda, A. Agrawal, J. Gans, and A. Goldfarb, Eds. Chicago, IL, USA: Univ. Chicago Press, 2019, pp. 197-236.
[12] A. Agrawal, J. Gans, and A. Goldfarb, Prediction Machines: The Simple Economics of Artificial Intelligence. Boston, MA, USA: Harvard Business Review Press, 2018.

[13] E. Brynjolfsson, D. Rock, and C. Syverson, “Artificial intelligence and the modern productivity paradox,” in The Economics of Artificial Intelligence, Chicago, IL, USA: Univ. Chicago Press, 2019, pp. 23-57.
[14] A. Felten, M. Raj, and R. Seamans, “Occupational, industry, and geographic exposure to artificial intelligence,” Strategic Manag. J., vol. 42, no. 12, pp. 2195-2217, 2021, doi: 10.1002/smj.3286.
[15] T. Eloundou, S. Manning, P. Mishkin, and D. Rock, “GPTs are GPTs: An early look at the labor market impact potential of large language models,” arXiv:2303.10130, 2023.
[16] N. Maslej et al., Artificial Intelligence Index Report 2024. Stanford, CA, USA: Stanford Institute for Human-Centered AI, 2024.
[17] OECD, OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market. Paris, France: OECD Publishing, 2023.
[18] World Bank, Digital Progress and Trends Report 2023. Washington, DC, USA: World Bank, 2023.
[19] International Monetary Fund, Gen-AI: Artificial Intelligence and the Future of Work. Washington, DC, USA: IMF, 2024.
[20] UNESCO, Recommendation on the Ethics of Artificial Intelligence. Paris, France: UNESCO, 2021.
[21] European Commission, Ethics Guidelines for Trustworthy AI. Brussels, Belgium: European Commission, 2019.
[22] M. Susskind, A World Without Work. New York, NY, USA: Metropolitan Books, 2020.
[23] A. J. Bessen, “AI and jobs: The role of demand,” NBER Working Paper no. 24235, 2018.
[24] M. Webb, “The impact of artificial intelligence on the labor market,” Stanford Univ. Working Paper, 2020.
[25] Ministry of Communication and Information of the Republic of Indonesia, Digital Indonesia Roadmap 2021-2024. Jakarta, Indonesia: Kominfo, 2021.