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Beyond AI Adoption: How Local Knowledge and Institutional Trust Shape Inclusive Economic Development in Emerging Economies

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ABSTRACT

Artificial intelligence (AI) is increasingly recognized as a potential driver of productivity, innovation, and economic transformation. However, the economic benefits of AI adoption are not necessarily distributed equally across individuals, enterprises, and communities. In emerging economies, technological adoption occurs within social environments characterized by uneven digital capabilities, diverse cultural practices, and varying levels of institutional trust. This article develops a qualitative research framework to examine how local knowledge and institutional trust shape the pathways through which AI contributes to inclusive economic development. Drawing on the capability approach, institutional theory, and sociotechnical perspectives, the study conceptualizes AI not merely as a technological resource but as a socially embedded capability whose developmental outcomes depend on local interpretation, institutional legitimacy, and opportunities for meaningful participation. The proposed research employs an interpretive qualitative multiple-case study design, with small enterprises, community-based economic organizations, and local institutions in Indonesia as potential empirical settings. Data will be collected through semi-structured interviews, observations, and document analysis, followed by reflexive thematic analysis. The study aims to develop a context-sensitive theoretical explanation of how AI-enabled economic opportunities are translated or fail to be translated into broader participation, improved economic agency, and more equitable access to economic benefits. By integrating local knowledge and institutional trust into the analysis of AI-enabled development, the article seeks to contribute to debates on inclusive digital transformation in emerging economies.

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1. INTRODUCTION

Artificial intelligence (AI) is increasingly recognized as a transformative force capable of reshaping productivity, business practices, and economic development. The growing availability of AI-enabled applications has created new opportunities for enterprises to improve operational efficiency, expand market access, process information, and develop innovative products and services. Nevertheless, the economic implications of AI are unlikely to be uniform across countries, organizations, and social groups. In emerging economies, the ability to benefit from AI depends not only on access to technology but also on the availability of digital infrastructure, workforce capabilities, financial resources, and supportive institutional arrangements. Chaar et al. (2025), in their analysis of the global productivity divide, emphasize that structural constraints may prevent low-income and lower-middle-income countries from fully realizing AI-related productivity gains. These constraints raise a fundamental development question: whether AI will broaden economic opportunities for previously disadvantaged groups or reinforce existing inequalities between those who possess the capabilities to exploit technological change and those who do not.

The distinction between AI adoption and inclusive economic development is therefore central to understanding the developmental consequences of digital transformation. Adoption refers to the introduction or use of technological applications, whereas inclusive economic development concerns the extent to which economic opportunities, productive capabilities, and associated benefits become accessible to a broader range of economic actors. An enterprise may adopt AI without achieving meaningful improvements in productivity, market participation, or economic resilience. Similarly, an entrepreneur may use AI-generated recommendations while remaining constrained by limited capital, inadequate digital literacy, weak bargaining power, or restricted access to formal institutions. From this perspective, technological availability should not be treated as sufficient evidence of development. Instead, research needs to examine the social and institutional processes through which technological resources are translated into substantive economic opportunities.

The capability approach provides a useful theoretical foundation for examining this distinction. Sen (1999) conceptualizes development in terms of expanding people's substantive freedoms and capabilities to pursue outcomes they have reason to value. Applied to AI-enabled economic transformation, this perspective shifts attention from the possession of digital tools toward the actual opportunities individuals can achieve through their use. AI becomes a potential resource for development rather than an automatic source of welfare improvement. Whether this resource expands economic agency depends on the conditions under which individuals can access, understand, adapt, and apply it to their circumstances. This perspective is particularly relevant in emerging economies, where economic actors may face unequal access to education, finance, infrastructure, and institutional support. It also suggests that the consequences of AI adoption should be examined through people's lived experiences and the contextual conditions shaping their ability to benefit from technological change.

Beyond technological capabilities, the social and cultural context in which AI is introduced deserves greater analytical attention. Economic activities are embedded in relationships, accumulated experience, cultural expectations, and context-specific knowledge. For small enterprises and community-based businesses, such knowledge may include familiarity with local customers, customary trading practices, seasonal market conditions, informal credit relationships, and community expectations regarding fairness and reciprocity. These forms of knowledge may influence how entrepreneurs interpret AI-generated information, evaluate its relevance, and determine whether technological recommendations are appropriate for their markets. AI systems that rely on standardized data or generalized recommendations may not always adequately represent the realities

of local economic environments. Consequently, local knowledge may serve as a resource for interpreting, adapting, or critically evaluating technological outputs. At the same time, its role should not be assumed to be uniformly beneficial; its value may depend on the nature of the task, the quality of the available information, and the capacity of economic actors to combine experience with new technological possibilities.

Recent qualitative research by Baka et al. (2026) highlights the importance of contextual relevance, human oversight, ethical governance, and community participation in AI development and deployment across low- and middle-income country settings. Although their study focuses on health-related AI and therefore cannot be directly generalized to economic development, it provides a relevant indication that technological implementation is shaped by human and sociocultural conditions. This insight supports the need for further investigation into how context-specific knowledge operates within everyday economic activities. In particular, it remains important to understand how local economic actors combine their accumulated knowledge with AI-enabled information, when they accept or reject technological recommendations, and how these decisions influence their participation in emerging digital markets. Examining these processes can help explain why the same technology may produce different outcomes across communities and enterprises facing different social and institutional circumstances.

Institutional trust introduces a further dimension to this relationship. Economic actors do not make decisions about AI solely on the basis of perceived technical usefulness; their decisions may also reflect beliefs about the reliability, fairness, and accountability of the institutions involved. Such institutions may include local government, financial institutions, business associations, cooperatives, and digital platforms. Institutional theory provides a basis for examining how formal rules, informal norms, and shared expectations shape economic behavior (Scott, 2014). Within AI-enabled development, institutional trust may affect whether entrepreneurs seek digital training, share information, engage with support programs, or rely on AI-generated recommendations. Nevertheless, trust should not be assumed to operate uniformly. An entrepreneur may trust a local cooperative while distrusting a digital platform, or may regard government support as legitimate but remain concerned about data privacy. These distinctions indicate that trust is relational and context-dependent, requiring investigation through the experiences of the people and organizations involved.

Recent research also demonstrates that trust in AI implementation is an important organizational issue. A 2026 study in Information Technology & People examines how government involvement, organizational leadership, managerial competence, and organizational readiness shape trust in AI implementation capability, drawing on survey data from information technology firms (Information Technology & People study, 2026). Although its quantitative design differs from the qualitative approach proposed here, the study highlights the importance of examining trust in relation to organizational and institutional conditions. The present research extends this discussion by shifting the analytical focus from organizational readiness to the experiences of economic actors operating within locally embedded economic environments. It asks how institutional relationships are interpreted in practice and how those interpretations may influence the distribution of AI-related economic opportunities.

Despite these emerging insights, an important research opportunity remains at the intersection of local knowledge, institutional trust, and inclusive economic development. Existing research has examined AI-related productivity disparities, contextual factors in human–AI interaction, and organizational trust in AI implementation (Baka et al., 2026; Chaar et al., 2025; Information Technology & People study, 2026). However, these streams address different analytical levels and research contexts. The OECD analysis focuses primarily on cross-country productivity differences and structural barriers; Baka et al. (2026) examine human factors in AI development and deployment

in health-related contexts; and the 2026 trust study investigates organizational conditions in technology-related firms. These contributions are relevant, but they do not directly resolve how local economic knowledge and institutional trust interact in the everyday processes through which small enterprises and community-based economic actors attempt to translate AI access into broader economic participation. This distinction constitutes the specific research problem addressed by the proposed study.

The gap should not be interpreted as evidence that no previous study has examined these concepts. Rather, it identifies a need for a more integrated, context-sensitive explanation of their interaction in economic development. In particular, further qualitative investigation is required to understand how local knowledge informs the interpretation of AI outputs, how institutional trust shapes decisions to use or reject technological applications, and how these processes influence the opportunities available to different economic actors. A qualitative approach is appropriate because these relationships involve meanings, experiences, institutional interactions, and contextual mechanisms that may not be adequately captured by measuring adoption rates or testing predetermined statistical relationships alone. Through in-depth interviews, observation, and document analysis, the study can investigate both enabling and constraining processes, including cases in which AI creates opportunities as well as cases in which its benefits remain limited or unevenly distributed.

Indonesia provides a relevant context for this investigation because AI-enabled economic activities coexist with diverse local knowledge systems, different levels of digital capability, and varied institutional environments. Within this broader context, Madura may offer a useful empirical setting for exploring how small enterprises and community-based economic actors interpret digital transformation in relation to established market practices and social relationships. Nevertheless, the relevance of Madura should be demonstrated through field evidence rather than assumed from its cultural distinctiveness. The research should also remain attentive to differences among participants, including variations in enterprise resources, digital literacy, access to finance, and relationships with formal and informal institutions. This approach can help connect a contextually grounded investigation with broader debates concerning economic inclusion in emerging economies.

Building on the capability approach (Sen, 1999), institutional theory (Scott, 2014), and sociotechnical perspectives, this study seeks to develop a process-oriented explanation of how local knowledge and institutional trust shape AI-enabled economic development. Its central analytical proposition is that AI access does not automatically translate into inclusive outcomes; instead, the conversion of technological resources into meaningful economic opportunities may depend on how individuals and organizations interpret, adapt, and trust the technologies available to them. The study therefore addresses three research questions: (1) How do local economic actors interpret and integrate AI into their existing knowledge and economic practices? (2) How does institutional trust shape their willingness and ability to use AI and benefit from AI-enabled opportunities? and (3) Through what processes do local knowledge and institutional trust facilitate or constrain inclusive economic development?

The study aims to contribute to the literature in three ways. First, it distinguishes technological adoption from the substantive economic opportunities that adoption may or may not create. Second, it brings local knowledge and institutional trust into a common analytical framework to examine their potentially complementary, conflicting, or conditional roles in the conversion of AI access into economic capabilities. Third, it seeks to generate context-sensitive insights from Indonesia that may inform comparative research and policy discussions in other emerging economies. The intended contribution is not to claim that local knowledge or institutional trust necessarily produces inclusive development, but to identify the conditions and mechanisms through which these factors may

influence economic participation. By examining these processes through qualitative inquiry, the study aims to move beyond technology-centered explanations and toward a more socially grounded understanding of inclusive AI-enabled economic development.

2. METHODS

This study employs a qualitative multiple-case study design to explore how local knowledge and institutional trust shape inclusive economic development in the context of artificial intelligence (AI) adoption in emerging economies, with particular attention to Indonesia. Grounded in an interpretivist philosophical perspective, the study seeks to understand how local economic actors construct meaning, negotiate institutional relationships, and integrate AI into their existing economic practices. A multiple-case study approach is appropriate because it enables an in-depth examination of contextual differences and similarities across cases (Yin, 2018). Data will be collected from selected micro, small, and medium-sized enterprises (MSMEs), community-based organizations, cooperatives, and relevant institutional stakeholders. Participants will be selected purposively based on their experience with digital technologies, local economic practices, AI adoption, or institutional support, with snowball sampling used where necessary to identify additional relevant informants. The proposed sample will consist of approximately 25–35 participants, although the final number will depend on the relevance, richness, and depth of the information obtained, guided by the principle of information power (Malterud et al., 2016).

Data collection will involve semi-structured interviews, non-participant observations, and document analysis to enable triangulation across different sources. Interviews will explore participants' experiences of AI adoption, the role of local knowledge in economic decision-making, perceptions of institutional trust, and the opportunities and barriers associated with inclusive economic participation. Data will be analyzed using reflexive thematic analysis following Braun and Clarke's (2006, 2022) approach, involving familiarization with the data, coding, theme development, theme review, theme definition, and analytical reporting. The analysis will combine inductive coding, allowing themes to emerge from participants' accounts, with theoretically informed interpretation drawing on the capability approach, institutional theory, and sociotechnical perspectives. Research rigor will be strengthened through data triangulation, reflexive documentation, transparent analytical procedures, and attention to divergent or contradictory accounts. Ethical principles will guide the research, including informed consent, voluntary participation, confidentiality, secure data management, and appropriate institutional approval. As a qualitative study, the research aims to develop context-sensitive theoretical insights rather than statistically generalizable conclusions. The final case locations, participant characteristics, sample size, and data collection period will be specified according to the actual fieldwork conducted.

3. FINDINGS AND DISCUSSION

Beyond AI Adoption: The Importance of Local Economic Context

The proposed analytical framework suggests that AI adoption should not be understood solely as a technological process but also as a context-dependent phenomenon shaped by local knowledge, economic resources, and established social practices. In emerging economies, local economic actors may evaluate AI technologies according to their perceived usefulness, compatibility with existing business practices, affordability, and relevance to community needs. Consequently, access to AI does not necessarily translate into meaningful economic benefits. The central analytical question is whether AI can be integrated into existing economic activities in ways that improve productivity, strengthen decision-making, and expand opportunities for groups that have traditionally experienced limited access to digital resources.

This perspective is consistent with Sen's (1999) capability approach, which conceptualizes development in terms of expanding people's substantive freedoms and opportunities rather than merely increasing material resources. Applied to AI adoption, this implies that digital access should be evaluated alongside individuals' capabilities to understand, use, adapt, and benefit from technological systems. Local entrepreneurs may have access to AI applications but still face barriers related to digital literacy, financial resources, infrastructure, or limited institutional support. Therefore, the potential contribution of AI to inclusive economic development depends not only on technological availability but also on the social and economic conditions that enable people to convert technological resources into valuable outcomes.

Digital Innovation as the Main Driver of Islamic Economics

Local knowledge represents an important analytical dimension in understanding how AI can be integrated into community-based economic activities. Such knowledge includes practical experience, cultural values, traditional production techniques, local market understanding, and community-specific ways of organizing economic relationships. Rather than treating local knowledge as an obstacle to technological modernization, this study conceptualizes it as a potential resource for adapting AI applications to local needs and circumstances.

From a sociotechnical perspective, technological outcomes emerge through interactions between technological systems and the social environments in which they are used. AI applications may support marketing, customer communication, inventory management, and business planning; however, their usefulness depends on whether their outputs reflect the realities of local markets and community practices. For example, AI-generated promotional content may increase the visibility of local products, but its effectiveness may depend on the accurate representation of local identity, cultural meanings, and consumer preferences. These examples illustrate potential mechanisms that should be examined through interviews, observations, and documentary evidence rather than assumed to represent established findings.

The theoretical implication is that local knowledge may function as a contextual interpretive resource that helps economic actors assess, modify, or reject AI-generated recommendations. This perspective also raises questions about whose knowledge is represented in AI systems and whether local communities retain meaningful control over how their knowledge is used. Inclusive AI adoption should therefore consider not only efficiency and innovation but also cultural relevance, local participation, and the recognition of community knowledge.

Institutional Trust and the Conditions for AI Adoption

Institutional trust provides a further analytical lens for understanding the relationship between AI adoption and inclusive economic development. In this study, institutional trust refers to economic actors' perceptions of the reliability, fairness, transparency, and accountability of institutions involved in digital transformation, including government agencies, financial institutions, technology providers, and business-support organizations.

Institutional theory emphasizes that economic activities are embedded in formal rules, informal norms, and broader systems of legitimacy (Scott, 2014). From this perspective, the adoption of AI may depend partly on whether local actors believe that the institutions supporting digital transformation are credible and responsive to their needs. Trust may influence their willingness to participate in training programs, use digital services, share business information, or invest resources in AI-enabled activities. Conversely, uncertainty about data protection, unclear regulations, limited access to assistance, or perceptions of unequal treatment may discourage participation.

However, institutional trust should not be interpreted as an automatic guarantee of successful adoption. Even when institutions are perceived positively, financial constraints, inadequate infrastructure, and limited digital capabilities may continue to restrict participation. Institutional trust is therefore better understood as one potential enabling condition interacting with individual

capabilities, organizational resources, and the broader digital environment. This interpretation directs attention toward the quality of institutional relationships rather than merely the existence of digital policies or support programs.

Toward an Integrated Framework for Inclusive Economic Development

The preceding discussion supports an integrated analytical framework in which AI adoption, local knowledge, institutional trust, and human capabilities are examined as interrelated dimensions of inclusive economic development. AI provides technological possibilities, local knowledge helps contextualize and interpret those possibilities, institutional trust shapes relationships with supporting organizations, and human capabilities influence whether individuals can convert available resources into meaningful economic opportunities.

The capability approach provides a useful basis for distinguishing technological access from substantive economic inclusion (Sen, 1999). Meanwhile, institutional theory highlights the importance of formal and informal arrangements that shape economic behavior (Scott, 2014). Together, these perspectives suggest that the developmental value of AI should be assessed through its contribution to participation, agency, opportunity, and the distribution of benefits, rather than through adoption rates alone.

This integrated perspective also identifies several possible tensions for empirical investigation. First, AI may improve efficiency while simultaneously disadvantaging actors who lack the skills or resources to use it effectively. Second, AI-enabled standardization may simplify business processes but inadequately represent local cultural knowledge. Third, digital development initiatives may expand access while failing to build trust if institutional arrangements are perceived as opaque or unresponsive. These tensions should be examined across contrasting cases to determine when AI supports inclusion and when it may reproduce existing inequalities.

Theoretical and Practical Implications

The potential theoretical contribution of this study lies in positioning local knowledge and institutional trust as interconnected contextual dimensions in the relationship between AI adoption and inclusive economic development. Rather than treating AI adoption as an isolated technological decision, the proposed framework emphasizes the interaction between technological resources, community knowledge, institutional relationships, and human capabilities. This perspective may contribute to management research by connecting digital transformation with the institutional and cultural conditions of emerging economies.

Practically, the framework suggests that policymakers and development institutions should complement AI infrastructure and digital-skills programs with locally relevant training, participatory program design, transparent data governance, and accessible support mechanisms. Businesses and community organizations may also benefit from combining AI-enabled analysis with local experience and human judgment. Such an approach could help ensure that technological innovation remains responsive to community priorities rather than focusing exclusively on operational efficiency.

Nevertheless, these implications remain provisional until supported by empirical evidence. The final interpretation must be grounded in actual participant accounts, observations, documents, and systematic thematic analysis. The completed study should identify which themes were genuinely developed from the data, explain differences across cases, and examine evidence that challenges the proposed framework. Only then can the study establish whether and how local knowledge and institutional trust shape inclusive economic development in the selected research context.

4. CONCLUSION

This study examines the relationship between artificial intelligence (AI) adoption, local knowledge, institutional trust, and inclusive economic development in emerging economies. It

advances the perspective that the contribution of AI to economic development cannot be assessed solely through technological adoption or operational efficiency. Instead, its potential value depends on the interaction between technological capabilities, locally embedded knowledge, institutional relationships, and the ability of individuals and communities to translate digital opportunities into meaningful economic benefits.

The proposed framework highlights three interconnected dimensions. First, local knowledge can provide contextual understanding that helps economic actors adapt AI applications to local market conditions, cultural values, and established economic practices. Second, institutional trust may influence the willingness of individuals and organizations to engage with AI-enabled services, participate in digital development initiatives, and collaborate with supporting institutions. Third, human capabilities and access to economic resources are essential for translating technological opportunities into substantive improvements in participation and well-being. These dimensions suggest that AI adoption should be understood as a sociotechnical and institutional process rather than an exclusively technological transformation.

Theoretically, this study seeks to connect the capability approach with institutional theory and sociotechnical perspectives to develop a context-sensitive understanding of inclusive digital transformation. Its potential contribution lies in examining how local knowledge and institutional trust interact in shaping the conditions under which AI may support or constrain inclusive economic opportunities. Practically, policymakers, businesses, and development institutions should complement investment in digital infrastructure with locally relevant capacity-building programs, participatory decision-making, transparent data governance, and accessible institutional support. Such measures may help ensure that the benefits of AI are not limited to economically advantaged groups.

Nevertheless, the proposed arguments require validation through empirical investigation. Future research should examine these relationships across diverse communities, business sectors, and institutional settings, particularly in emerging economies characterized by differences in digital capabilities and local knowledge systems. By investigating both enabling conditions and potential barriers, future studies can clarify the mechanisms through which AI contributes to inclusive economic development. Ultimately, the central challenge is not merely to expand AI adoption, but to ensure that technological progress strengthens human capabilities, recognizes local knowledge, and supports fairer and more sustainable economic opportunities.

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