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Research Article [OPEN ACCESS]

Exploring the Affordances of AI-Enabled Livestock Monitoring Systems in Rural Agricultural Communities

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ABSTRACT

Productivity and sustainability remain persistent challenges in livestock farming across developing countries, particularly in rural contexts where digital transformation progresses unevenly. Advances in artificial intelligence (AI) offer opportunities to support livestock management; however, empirical understanding of how such technologies are perceived and utilized in rural settings remains limited. This study examines the perceived affordances of an AI-enabled livestock monitoring system in a rural community in Central Java, Indonesia. Guided by the Technology–Organization–Environment (TOE) framework, a qualitative case study approach was employed using semi-structured interviews with livestock farmers and local government officials. The findings indicate that the realization of AI-related affordances is shaped by technological conditions, including system capabilities, infrastructure limitations, and user readiness. Organizational factors—such as innovation awareness, government–community relationships, and the continuity of support programs—also influence affordance realization. Environmental conditions, particularly training adequacy, public trust, and rural geographic characteristics, further affect technology use. Overall, the study highlights that AI affordances in rural livestock systems are socio-technical and context-dependent, emphasizing the importance of context-sensitive design and implementation strategies to support sustainable livestock management.

Keyword: Artificial intelligence, livestock monitoring, technology adoption

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1. INTRODUCTION

Artificial Intelligence (AI) has emerged as a major technological advancement aimed at enhancing efficiency, accuracy, and decision-making across multiple sectors, including agriculture and livestock production (Alzubi & Galyna, 2023; Maragno et al., 2023). Within the agricultural sector, livestock production systems represent a critical component of global food security, as they directly contribute to the supply of protein and rural livelihoods (Ruthenberg & Hudson, 1981). In recent years, food security and self-sufficiency have gained increasing global attention, prompting countries to strengthen control over their food supply chains to meet domestic demand (Hassoun et al., 2022). This trend is particularly evident in developing economies, where rising incomes have been accompanied by increased consumption of livestock products (Sachs et al., 2022). Supporting this trend, World Bank data indicate that average GDP growth reached 4.5% in least developed countries and 3.6% in low- and middle-income countries in 2022 (World Bank, 2023).

Despite this growing demand, many developing countries continue to face structural challenges in meeting livestock production needs, primarily due to limited adoption of modern technologies that could enhance productivity and efficiency (Fuentes et al., 2022). The implementation of digital solutions in the agricultural sector remains constrained by inadequate technological infrastructure, including limited access to digital tools, data systems, and monitoring technologies (Bhattacharya, 2019). Technologies such as livestock monitoring systems, digital data management, and AI-supported productivity tools have been recognized as essential enablers of modern livestock management (Chimakurthi, 2019). However, insufficient investment and fragmented implementation strategies have restricted the potential of these technologies to contribute meaningfully to food security and sustainable agricultural development.

Recent studies suggest that physical infrastructure alone is no longer the primary barrier to digital technology adoption in developing countries (Tong et al., 2022). Instead, growing evidence highlights the importance of human capabilities—particularly digital skills, knowledge, and adaptive capacity—in determining whether technologies are effectively utilized (Anadozie et al., 2021). While existing research has identified various technological, organizational, and social factors influencing digital adoption, the literature remains fragmented and often lacks an integrated explanation of why digital transformation in rural and agricultural contexts progresses unevenly across developing regions (Pan & Zhang, 2020).

To address this gap, this study adopts the Technology–Organization–Environment (TOE) framework (Tornatzky et al., 1990) as a holistic analytical lens to examine the perceived affordances of AI-enabled technologies in the livestock sector of developing countries. Specifically, the study explores the implementation and use of an AI-based cattle monitoring system within livestock farmer communities and local government institutions in Maribaya Village, Brebes Regency, Central Java, Indonesia. By examining technological, organizational, and environmental factors shaping the adoption and use of this system (Fuentes et al., 2022), this research seeks to contribute empirical insights into rural AI adoption and agricultural digitalization. The study employs a case study approach to capture contextual dynamics and stakeholder perspectives in depth (Yin, 2018).

2. MATERIALS AND METHODS

2.1 Materials

The study was conducted in Maribaya Village, Brebes Regency, Central Java, Indonesia. The empirical setting involved a livestock farming community and local government institutions participating in an initiative to introduce an AI-based cattle monitoring system. The system was designed to support the estimation of cattle body weight as an input for livestock pricing and management practices.

The overall project was carried out from February to December 2023. Empirical materials reported in this study were collected during two field visits conducted in March and October 2023. The first visit focused on understanding local conditions and assessing the feasibility of introducing digital technologies for livestock management, while the second visit aimed to deepen stakeholder engagement and support preparatory activities related to the prospective use of the AI-based monitoring system.

Primary data were obtained through semi-structured interviews with eight participants, consisting of livestock farmers and local government officials directly involved in or affected by the AI implementation. Participant characteristics, including role, age, and educational background, are presented in Table 1. Informal discussions with community members and district-level actors were used as supplementary materials to enrich contextual understanding.

Participants were selected using purposive sampling to ensure representation of key stakeholder groups relevant to the implementation of the AI-based livestock monitoring system. Selection criteria were based on participants' direct involvement in livestock management activities or institutional responsibilities related to agricultural development at the local level. This approach ensured that the empirical materials reflected practical experiences and contextual knowledge relevant to the study objectives.

Table 1. Profile of research interviewees

Respondent	Role	Age (years)	Educational Background
R1	Farmer	31	Animal Husbandry
R2	Farmer	27	High School
R3	Government Official	56	Veterinary Medicine
R4	Government Official	25	Animal Husbandry
R5	Government Official	26	Animal Husbandry
R6	Farmer	31	High School
R7	Farmer	35	High School
R8	Farmer	39	High School

2.2 Methods

A qualitative case study design was adopted to capture in-depth perspectives on how AI technology is perceived, introduced, and situated within local livestock management practices. This design enabled an exploration of contextual factors and stakeholder interpretations that are difficult to capture through quantitative approaches.

Data were collected through semi-structured interviews conducted during both field visits. Interview questions focused on participants' experiences, expectations, and concerns related to the AI-based monitoring system, including technological readiness, organizational support, training, and environmental constraints. All interviews were audio-recorded with participant consent and subsequently transcribed for analysis.

The Technology–Organization–Environment (TOE) framework was employed as an analytical lens to guide data interpretation. The technological dimension captured system capabilities, infrastructure readiness, and compatibility with existing practices. The organizational dimension examined stakeholder roles, government involvement, and the continuity of supporting programs. The environmental dimension focused on training adequacy, public trust, and geographic conditions influencing implementation. Given that rural contexts in developing countries are characterized by distinctive regulatory arrangements, varying levels of government support, and informal institutional practices (Ramadani & Almaarif, 2022), attention to local structures and actors is essential for understanding the broader environmental conditions shaping the affordances of agricultural AI.

Data analysis followed established qualitative procedures (Corbin & Strauss, 2014; Miles et al., 2014). Interview transcripts were first subjected to open coding to identify relevant concepts. These codes were then grouped into pattern codes and abstracted into higher-level categories aligned with the TOE dimensions. This iterative process facilitated the identification of recurring themes and cross-actor patterns related to conditions enabling or constraining the use of the AI system.

3. RESULTS AND DISCUSSION

3.1 Technological Domain

The analysis indicates that the perceived affordances of the AI-enabled livestock monitoring system in Maribaya Village are shaped by several technological conditions. These conditions relate to (1) stakeholders' perceptions of the system's technological capabilities based on current technology use, (2) limitations in technological infrastructure and digital readiness, and (3) expectations regarding future technology-enabled practices.

The first technological condition concerns the perceived potential of digital technology to support and optimize livestock management activities. Interview data show that existing technology use remains limited but has begun to support basic functions such as livestock recording and documentation. Respondents highlighted that AI-based systems could further enable more systematic record-keeping and provide access to relevant livestock information, including cattle body weight, pricing references, age, and breeding history, which are currently managed through manual practices. As expressed by one government official:

"Because the majority of people are engaged in farming and animal husbandry, I believe the technology has strong potential. It could be used for recording and documentation. If more advanced technology is developed, farmers could access information such as body weight, pricing, age, and breeding history, which would be beneficial for the community." (Respondent 5)

Despite this perceived technological potential, respondents emphasized that the realization of these affordances is constrained by limited technological readiness at the user level. Low levels of smartphone use and continued reliance on traditional transaction practices remain common among farmers. These conditions limit farmers' ability to fully engage with technology-enabled livestock management practices. As noted by the same respondent:

"When we talk about Maribaya, most people still rely on traditional practices. Smartphone use is still limited, and many transactions continue to use conventional credit systems." (Respondent 5)

In addition to user-related constraints, technological implementation was perceived to depend on institutional arrangements for data management. Respondents stressed that the effective use of AI-enabled systems requires formal mechanisms to ensure that livestock data are consistently recorded, maintained, and validated by local government institutions. This reflects the need for organizational involvement to support technological affordances beyond individual farmers' capabilities. As one participant explained:

"We need to ensure that the data are recorded and maintained by the local government. We cannot rely only on farmers' individual knowledge." (Respondent 7)

Finally, respondents viewed existing technological and geographic challenges as drivers for future technological innovation. As shown in Figure 1, expectations for future development include wearable monitoring devices and automated surveillance systems to support livestock monitoring across large and geographically dispersed areas. These anticipated innovations were perceived as potentially enabling more efficient monitoring practices and reducing existing operational constraints. As expressed by a farmer:

"We hope that in the future the system can make our work easier, especially because monitoring livestock across large areas is difficult under current conditions." (Respondent 1)

3.2 Organizational Domain

From an organizational perspective, the findings indicate that the realization of perceived affordances was primarily shaped by the awareness and involvement of local government institutions, as well as by their relationships with livestock farming communities. As illustrated in Figure 1, three interrelated organizational conditions were identified: (1) organizational awareness of the importance of innovation, (2) relationships between government actors and farmers' communities, and (3) the continuity and sustainability of supporting programs.

The first organizational condition concerns awareness of the importance of innovation in the context of rural digital transformation. Respondents emphasized that local government institutions actively promote innovation as part of broader digitalization efforts, including initiatives aimed at improving connectivity and supporting community-based economic activities. As stated by one government official:

"We are moving toward innovation, and this innovation also comes from within our organization. We are actively directing it in response to the digitalization era, including collaboration with Telkom to improve internet access in remote areas. Through this, we aim to develop a smart village that supports various community activities, including buying and selling." (Respondent 3)

The second organizational condition relates to the relationship between government institutions and farmers' communities in implementing AI-related technologies. Respondents highlighted the importance of institutional commitment and informal coordination between government staff and local farmers to support technology introduction and use. In this regard, government readiness to engage directly with livestock farmers through outreach and facilitation was viewed as essential. As explained by Respondent 5:

> *"This application is mainly intended for livestock farmers, but the local government is also ready to provide outreach and support to the community."* (Respondent 5)

Finally, respondents emphasized the importance of continuity and sustainability of supporting programs. The effective use of AI-based livestock monitoring systems was perceived to depend on sustained institutional support, including ongoing training, technical assistance, and adequate budgeting. Without long-term commitment from local government and related private-sector partners, respondents expressed concern that the perceived benefits of the system would be difficult to maintain in practice.

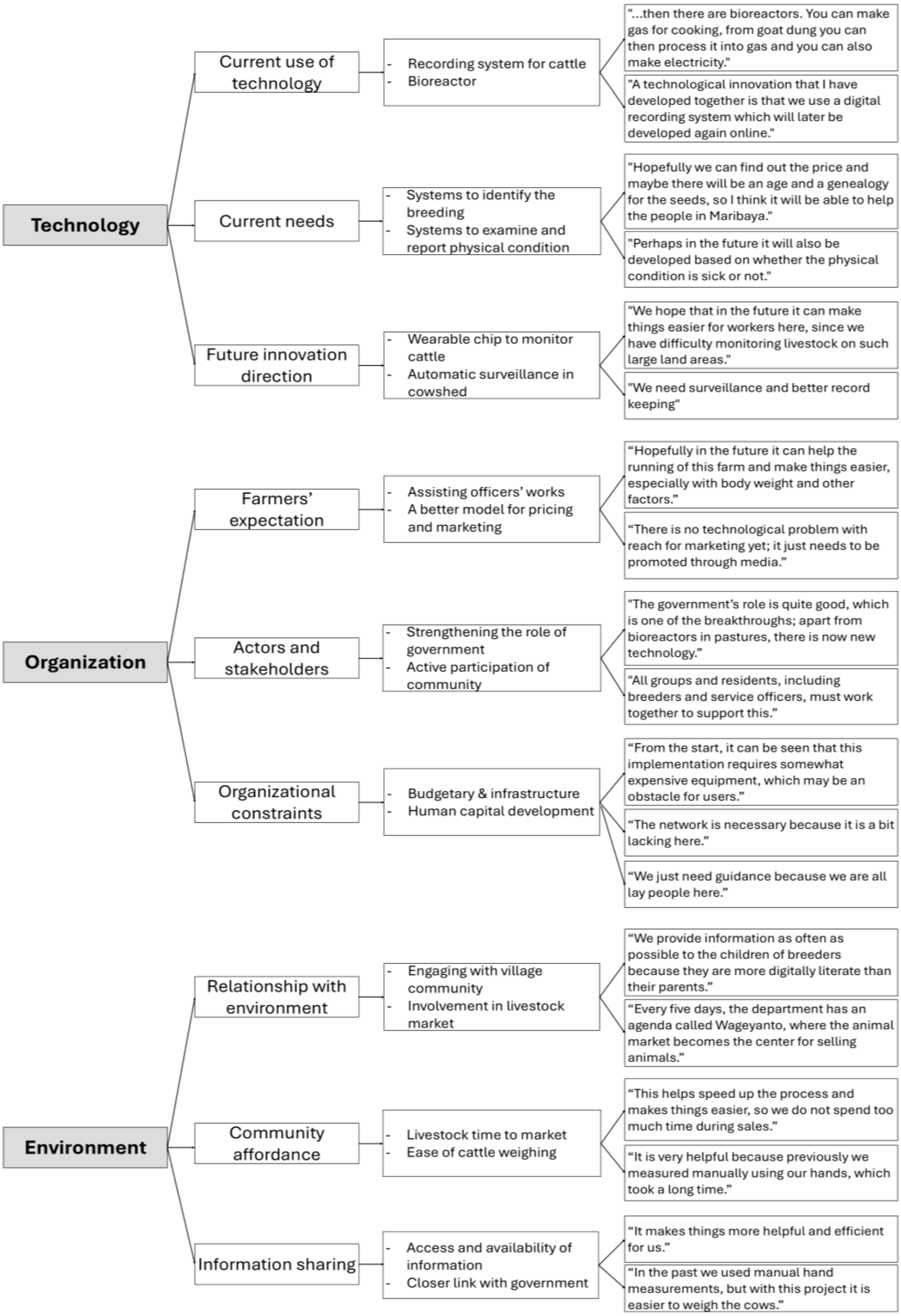

Figure 1. Coding structure of technological, organizational, and environmental domains

3.3 Environmental Domain

From an environmental perspective, the analysis shows that the realization of perceived affordances was influenced by several contextual factors, including (1) the adequacy of training and facilitation, (2) public trust in technological innovation, and (3) the geographical characteristics of the rural environment.

The first environmental factor relates to the adequacy of training and facilitation provided to livestock farming communities. Respondents emphasized that effective implementation of AI-based systems requires sufficient training and continuous guidance, particularly given the limited prior exposure of farmers to digital technologies. As noted by one respondent:

> *"This application is mainly intended for livestock farmers, since they are the direct users and will have the most access to it. At the same time, the department is ready to provide socialization and facilitation, which is also beneficial for institutional activities, especially in the livestock market."* (Respondent 5)

In addition to training-related factors, respondents expressed generally positive perceptions of the potential benefits of the system, which contributed to growing trust in the innovation. Several participants noted that AI-enabled monitoring could improve efficiency and reduce reliance on time-consuming manual practices. As explained by a farmer:

> *"It is quite helpful, because previously traders and breeders used manual methods that were inefficient. With this system, processes can be faster and easier, so we do not spend too much time during transactions."* (Respondent 1)

Despite these positive perceptions, respondents also highlighted environmental constraints associated with the geographical conditions of Maribaya Village. The rural setting, characterized by dispersed livestock locations and challenging terrain, was seen as a barrier to technology deployment. Moreover, limited awareness of technological advancement among community members was identified as an additional environmental challenge. As stated by Respondent 5:

> *"In terms of challenges, the most difficult issues are the geographical conditions and the relatively low awareness among people in Maribaya regarding the importance of technological progress."* (Respondent 5)

3.4 Discussion

The findings of this study, interpreted through the Technology–Organization–Environment (TOE) framework, are broadly consistent with recent research on the adoption of AI-based technologies in agricultural contexts within developing countries. At the technological level, perceived system capabilities emerged as a central factor shaping adoption-related outcomes, reinforcing prior studies that highlight the role of AI-enabled technologies in supporting sustainable agricultural practices (Lakshmi & Corbett, 2023). At the same time, limitations in technological infrastructure continue to represent substantial barriers, echoing challenges reported in studies on UAV deployment in rural India (Puppala et al., 2023) and the implementation of smart farming technologies in resource-constrained settings (Osrof et al., 2023). In line with prior work, the present findings further indicate that users' digital readiness and perceived usability strongly influence how AI-related action possibilities are recognized and engaged with by small-scale farmers (Cimino et al., 2024; Dixit et al., 2023).

The importance of technology compatibility, ease of use, and digital literacy identified in this study also aligns with research emphasizing capacity building and human–AI complementarity as prerequisites for effective technology adoption (Issa et al., 2022; Mannuru et al., 2025). From an affordance perspective, these findings support the view that affordances are inherently relational: although AI technologies may introduce new possibilities for action, such as improved livestock monitoring or record-keeping, these possibilities can only be realized when users possess the necessary skills and when technologies are compatible with existing practices (Osrof et al., 2023). Without such enabling conditions, the potential benefits of AI remain latent rather than actionable within rural agricultural settings.

At the organizational level, the findings regarding innovation awareness, government–community relationships, and the sustainability of support programs are consistent with prior studies. Awareness-building initiatives have been shown to play a crucial role in reducing knowledge gaps and fostering adoption readiness among farmers (Cimino et al., 2024; Puppala et al., 2023). Similarly, the importance of government involvement and collaborative relationships supports existing evidence advocating for stronger public–private partnerships in agricultural digitalization efforts (Lakshmi & Corbett, 2023; Mannuru et al., 2025). The emphasis on continuity and long-term institutional support further reflects earlier findings that sustained training and program persistence are necessary to prevent early-stage adoption from declining over time (Issa et al., 2022; Osrof et al., 2023). In this sense, organizational conditions do not merely function as external supports, but actively shape whether AI-related affordances become visible, legitimate, and usable for rural actors.

Finally, the environmental dimension of the findings highlights the role of training adequacy, public trust, and geographic characteristics in shaping AI adoption outcomes. Consistent with previous studies, adequate training and facilitation were found to be essential for enabling users to engage meaningfully with AI-based systems (Lakshmi & Corbett, 2023; Puppala et al., 2023). Trust in technological reliability and transparency also emerged as a key factor influencing acceptance, reinforcing calls for human-centered and context-sensitive AI implementations in agricultural settings (Cimino et al., 2024; Mannuru et al., 2025). Moreover, the influence of rural geographic conditions aligns with existing research that underscores the need to address physical infrastructure and spatial constraints when deploying AI technologies in remote areas (Issa et al., 2022; Osrof et al., 2023). Taken together, these environmental factors underscore that AI affordances do not reside in technological features alone, but depend on socio-technical and physical contexts that render action possibilities visible and practically achievable for farmers (Muhdiantini et al., 2024).

Taken together, these findings indicate that the adoption of AI-enabled livestock monitoring systems in rural contexts should be understood as a socio-technical process rather than a purely technological intervention. The extent to which AI-related action possibilities become meaningful in practice depends on the alignment between technological capabilities, organizational arrangements, and environmental conditions. This integrated perspective extends prior adoption-focused studies by demonstrating that affordances do not operate independently of context, but are shaped by local readiness, institutional support, and infrastructural constraints. By employing the TOE framework to interpret the realization of affordances, this study underscores the importance of designing and implementing AI systems in ways that are sensitive to local capacities and governance structures, thereby increasing the likelihood that AI-enabled innovations contribute to sustainable livestock management in rural settings.

4. CONCLUSION

This study examined the implementation and use of AI-based livestock monitoring systems in rural areas of developing countries by adopting the Technology–Organization–Environment (TOE) framework as an analytical lens. Rather than treating affordance as an independent factor, the study identified technological, organizational, and environmental conditions that shape how the affordances of AI-enabled systems are perceived and realized in practice. From a technological perspective, the findings indicate that perceived system capabilities, limitations in technological infrastructure, and users' readiness to engage with technology-enabled practices play a critical role in determining whether AI-related action possibilities can be effectively utilized. At the organizational level, awareness of innovation, the quality of relationships between government institutions and farming communities, and the continuity of supporting programs were found to influence how these affordances are legitimized and sustained. From an environmental perspective, the adequacy of training and facilitation, public trust in innovation, and the geographical characteristics of rural settings further shape the extent to which AI-enabled affordances become actionable.

The findings also yield several important practical implications. First, local and national governments should prioritize the improvement of technological infrastructure in rural areas, particularly network connectivity and supporting facilities, to enable farmers to access and interact with AI-based systems more effectively. Second, sustained training, mentoring, and awareness-building programs are essential to enhance farmers' understanding of AI technologies and to support their integration into existing livestock management practices. In addition, governments should strengthen collaborative relationships with farming communities by acting as facilitators in technology deployment and by ensuring adequate financial resources to support system implementation and maintenance.

Based on these findings, it is recommended that governments and relevant stakeholders adopt a coordinated approach to rural AI adoption. This includes reinforcing collaboration among government institutions, farming communities, technology providers, and academic partners to foster a supportive innovation ecosystem. Financial incentives and long-term funding mechanisms are necessary to reduce cost barriers and ensure program sustainability. Finally, AI system design and implementation should be adapted to local geographical, cultural, and operational contexts and should be periodically evaluated to ensure that the perceived affordances of AI technologies translate into sustainable and long-term benefits for livestock management in rural areas. Future research may extend this study by examining affordance realization across multiple rural contexts or by integrating quantitative approaches to assess adoption outcomes over time. In addition, comparative studies across regions or agricultural sectors could provide deeper insights into how contextual variations shape the realization of AI-related affordances. Such efforts would further strengthen the empirical foundation for designing context-sensitive AI interventions in rural development.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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