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Analysis of Readiness Factors Influencing IoT Adoption in the Broiler Industry: Economic Implications in Malang Raya

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Abstract. This study aims to investigate the readiness factors influencing the adoption of Internet of Things (IoT) technology in the broiler industry in Malang Raya, East Java, with a focus on economic implications for local poultry farmers. A total of 100 broiler farmers were selected using purposive sampling, based on criteria of having operated their business for at least one year and willingness to complete the questionnaire. Survey data were tabulated and verified using Microsoft Excel, while demographic data were visualized. To examine relationships between variables—knowledge of IoT (X1), access and resources (X2), attitude toward technology (X3), and economic barriers (X4)—Structural Equation Modeling–Partial Least Squares (SEM–PLS) was applied using SmartPLS software. The findings revealed that knowledge (X1) and attitude (X3) significantly influenced IoT adoption readiness, with knowledge being the most dominant factor. The model explained 72.7% of the variance in IoT adoption decisions ($R^2 = 0.727$). The findings revealed that knowledge and perception of IoT (X1) had the strongest and statistically significant influence (path coefficient = 0.400; $t = 2.095$; $p = 0.036$), while access and resources (X2), readiness and attitude toward technology (X3), and economic constraints (X4) did not show significant effects ($p > 0.05$). Strengthening farmers' understanding of IoT and building positive attitudes toward technology are essential strategies. Collaborative support from government, academia, and technology developers is recommended to achieve inclusive and sustainable IoT integration, thereby enhancing the economic competitiveness of smallholder poultry farming.

1 Introduction

Digital transformation has become a crucial catalyst in improving productivity and efficiency across various industrial sectors, including agriculture and livestock [1–2]. Over the past ten years, the Internet of Things (IoT) has become a key focus in the advancement of smart agriculture technologies, facilitating the immediate gathering, processing, and analysis of data through sensors, software, and network connectivity. In the poultry sector, particularly broiler farming, IoT implementation holds significant potential for optimizing

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farm management through automated monitoring of temperature, humidity, air circulation, feed consumption, and animal health conditions [3,4].

This technology is considered a promising solution to several challenges faced by smallholder farmers, such as resource efficiency, early disease detection, and reduction in poultry mortality rates [5–7]. Furthermore, integrating IoT into farm management systems contributes to increased productivity, reduced operational costs, and enhanced competitiveness—factors that may lead to improved economic returns for farmers and the agribusiness sector at large. It also supports sustainability goals in animal-based food production [8,9]. However, the adoption of IoT among smallholder farmers in developing countries like Indonesia still encounters significant structural and cultural barriers, which can affect the economic impact of this technological innovation [10,11].

Malang Raya, which comprises the administrative areas of Malang City, Malang Regency, and Batu City, is one of the major centers for broiler farming in Indonesia [12]. Most broiler production in this region is carried out by small- to medium-scale farmers who still rely on traditional management practices [13]. Although technology is increasingly accessible, and the cost of access is gradually declining, digital technology adoption—including IoT—remains very limited among these farmers. Based on our preliminary field observations, none of the broiler farmers in Malang Raya have fully adopted IoT systems; the current use is still partial, such as internet-connected CCTV, while advanced functions like automated disease detection or integrated environmental monitoring have not yet been implemented. This condition demonstrates a significant gap between technological potential and actual adoption, thereby reinforcing the importance of this study.

Previous research has highlighted that the successful uptake of new technologies is shaped by various psychological, social, and economic influences. In the case of IoT adoption in poultry farming, factors like technological understanding and perception, resource availability, openness to innovation, as well as economic costs and limitations, play crucial roles in determining adoption choices. Therefore, a deep understanding of these factors is crucial for designing targeted interventions, particularly for smallholder farmers who often face limitations in infrastructure, capital, and technical support [14,15].

This research seeks to examine the factors that impact the willingness to adopt IoT technology in broiler farm management among smallholder farmers in Malang Raya, East Java, Indonesia—an area that has not been thoroughly explored in current literature. Employing a quantitative approach and path analysis, the study assesses crucial factors influencing IoT adoption readiness, such as knowledge, perceptions, access to resources, and economic obstacles. The primary contribution of this research is to offer fresh perspectives on the challenges of IoT adoption in developing nations and to suggest policy recommendations focused on enhancing digital literacy and providing technical training to boost smallholder readiness for technological change.

2 Materials and methods

This study employs a quantitative approach using a survey method to explore and analyze the factors influencing the readiness for adopting IoT technology in broiler farm management among smallholder farmers in Malang Raya [16]. A quantitative approach was chosen as it produces objective and measurable data, and allows for generalization of the phenomenon under study, thereby providing broader and more reliable insights [17,18]. Ethical approval for this study was obtained (Ethics Approval Number: E.5.b/119-RPK-UMM/IX/2024), and data collection was conducted from October 1, 2024, to December 25, 2024.

The study population includes broiler farmers in the Malang Raya region, which encompasses Malang City, Malang Regency, and Batu City—areas recognized as some of the largest poultry farming centers in East Java. The sample was selected using purposive sampling, with the criteria of farmers who (i) have operated a broiler business for at least the past year, (ii) own a minimum population of approximately 2,000 broiler chickens, and (iii) are willing to complete the questionnaire in full. A total of 100 respondents meeting these criteria were selected as the sample [19,20].

The primary data collection instrument was a closed-ended questionnaire, developed based on five constructs: (X1) Knowledge and Perception of IoT Technology, (X2) Access and Resources, (X3) Readiness and Attitude Toward New Technology, (X4) Economic Costs and Barriers, and (Y) Adoption Intentions and Decisions for IoT. Each construct was measured using a set of indicators with a five-point Likert scale to assess respondents' level of agreement [21,22].

After data collection, the questionnaire results were tabulated and processed using Microsoft Excel for initial verification, coding, and demographic data visualization [23,24]. Characteristics of the farmers, such as their distribution across the Malang Raya region, the size of their broiler populations, proximity of poultry farms to residential areas, types of manual and automated poultry houses, and readiness to adopt IoT, were illustrated in diagrams to clarify the existing conditions.

To examine the interactions between the variables, Structural Equation Modeling–Partial Least Squares (SEM–PLS) was utilized with the help of SmartPLS software. The analysis was conducted in two key phases: initially, an algorithm test was performed to assess construct validity, indicator reliability, and R-square values; subsequently, a bootstrap test was conducted to evaluate the statistical significance of the relationships among the variables using path coefficients and t-statistics [25,26].

3 Results and discussion

3.1 Inner model

Figure 1 presents the inner model or structural model, which illustrates the causal relationships among the latent constructs. This model demonstrates the influence of the exogenous constructs (X1, X2, X3, and X4) on the endogenous construct (Y). Each path is accompanied by a path coefficient and a corresponding t-statistic value (in parentheses), indicating the strength and significance of the relationship. For example, X1 exerts the strongest influence on Y, with a coefficient of 0.400 and a t-value of 3.810, suggesting a statistically significant effect. In contrast, X2, X3, and X4 show smaller influences, with coefficients of 0.172 ($t = 1.518$), 0.144 ($t = 1.313$), and 0.144 ($t = 1.314$), respectively, which are likely not statistically significant.

3.1.1 Coefficient of determination

Table 1 presents the coefficient of determination (R-square) and adjusted R-square values for the dependent variable, namely the Intention and Decision to Adopt IoT (Y). The analysis results show that the R-square value of 0.727 indicates that 72.7% of the variation in farmers' decisions to adopt IoT technology can be explained by the four independent variables: (X1) Knowledge and Perception of IoT, (X2) Access and Resources, (X3) Readiness and Attitude toward New Technology, and (X4) Cost and Economic Constraints.

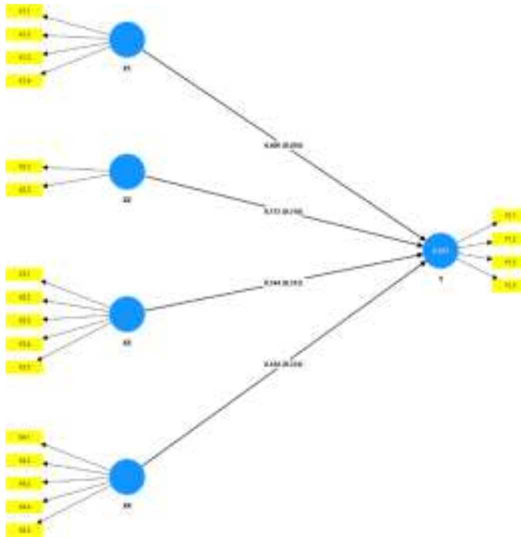

Fig. 1. Inner model, X1: Knowledge and Perception, X2: Access and Resources, X3: Readiness and Attitude, X4: Cost and Economic Constraints, and Y: IoT Adoption Decision

Table 1. Coefficient of determination of the dependent variable

Variable	R-square	R-square adjusted
Y	0.727	0.715

The adjusted R-squared value of 0.715 demonstrates the proportion of variance in the dependent variable (Y) that is accounted for by the four independent variables, after controlling for the number of predictors included in the model. This result indicates that the structural model exhibits a high level of predictive accuracy [27] with the independent variables collectively exerting a significant influence on the decision to adopt IoT technology among broiler farmers in the Greater Malang region.

3.1.2 Bootstrapping results for significance testing of path relationships

Table 2 presents the results of the bootstrapping analysis used to test the significance of the relationships among variables in the structural model. Of the four independent variables analyzed, only X1 (Knowledge and Perception of IoT Technology) has a significant influence on the dependent variable Y (Intention and Decision to Adopt IoT). This is indicated by the t-statistic value of 2.095 and a p-value of 0.036, which is below the significance threshold of 0.05 [28,29]. Therefore, it can be concluded that farmers' knowledge and perception play a crucial role in driving the decision to adopt IoT technology.

Meanwhile, the other three variables—X2 (Access and Resources), X3 (Readiness and Attitude toward New Technology), and X4 (Cost and Economic Constraints)—do not show a significant influence on the adoption decision, as indicated by the p-values exceeding 0.05. Specifically, the p-values are 0.158, 0.313, and 0.334, with t-values below the critical threshold of 1.96. These results suggest that, although these factors contribute to the model, their influence on the IoT adoption decision is not statistically strong within the context of the broiler farmers population in the Greater Malang area [30].

Table 2. Bootstrapping results for significance testing of path relationships

Variables	Original sample	Sample mean (M)	Standard deviation	*t*-statistics	*p*-values
X1 -> Y	0.400	0.394	0.191	2.095	0.036
X2 -> Y	0.172	0.176	0.122	1.412	0.158
X3 -> Y	0.144	0.151	0.143	1.009	0.313
X4 -> Y	0.184	0.181	0.190	0.966	0.334

3.2 Interpretation of analysis results

This study investigates the influence of four external factors (X1, X2, X3, and X4) on the readiness for adopting IoT technology in the smallholder livestock sector. The analysis results reveal that these four factors collectively explain 72.7 % of the variability in IoT adoption readiness, with an R^2 value of 0.727. These findings suggest that there are additional variables outside the current model that may significantly contribute to influencing farmers' readiness to adopt IoT technology [31].

Among the four factors, knowledge about IoT (X1) exerts the strongest and most statistically significant influence on adoption readiness, with a coefficient of 0.400 and a t-value of 3.810. This implies that the greater the farmers' understanding of IoT—particularly its benefits in enhancing operational efficiency and real-time monitoring—the more prepared they are to adopt the technology. In contrast, the other three factors—access and resources (X2), attitude toward new technology (X3), and cost and economic constraints (X4)—demonstrate weaker and statistically insignificant effects [32,33]. The access and resources factor (X2) shows a coefficient of 0.172 (t = 1.518), while both the attitude toward new technology (X3) and cost and economic constraints (X4) have coefficients of 0.144 with similar t-values (1.313 and 1.314, respectively).

These results indicate that, while cost and access are conceptually relevant, their influence on IoT adoption readiness is not statistically significant in the Malang Raya context. This contrasts with several studies in Indonesia and globally that identify cost and infrastructure as major barriers. For example, Swain et al. [5] and Ojo et al. [6] highlight that high investment costs and limited digital infrastructure are persistent obstacles in livestock IoT implementation. Similarly, research in Thailand and Malaysia shows that affordability and rural internet connectivity significantly affect farmers' readiness [34–37]. Studies from Bahrain and other Middle Eastern countries also emphasize the importance of economic resources and access in shaping ICT adoption.

However, our results align with studies showing that cognitive and attitudinal factors can outweigh infrastructural concerns in certain contexts. For instance, Chuang et al. [38] in Taiwan and Jabbari et al. [39] in Saudi Arabia found that farmers' knowledge and perception of technology had a more decisive role than cost in early adoption stages. Likewise, Bahari et al. [40] stress that understanding the tangible benefits of IoT can strongly drive adoption, even when financial or infrastructural challenges exist.

Therefore, the discrepancy between our findings and those of previous studies may reflect contextual differences. In Malang Raya, where internet connectivity is gradually improving and partial technology use (e.g., CCTV, automated feeders) is already familiar to some farmers, cost and access are not perceived as the primary challenges. Instead, the lack of awareness, digital literacy, and confidence in applying IoT solutions appears to be more critical. This underlines the importance of strengthening farmers' knowledge and attitudes through training and targeted capacity-building, while simultaneously supporting infrastructure and affordability to accelerate inclusive IoT adoption in the broiler industry.

3.3 The most significant factor influencing IoT adoption readiness

The Knowledge about IoT factor (X1) is the only factor that has a significant influence on IoT adoption readiness in smallholder livestock farming. This finding underscores the importance of technological literacy for farmers in adapting to technological changes. Reference [31] highlights that knowledge of IoT technology is a key factor in motivating individuals to adopt IoT services, particularly in informal settlement areas. A deep understanding of the direct benefits of IoT technology, such as operational efficiency and improved livestock management quality, encourages individuals to be more open to change.

According to reference [32], in the context of higher education, this finding is also relevant, as it suggests that students' readiness to adopt digital technologies like IoT influences their intention to integrate technology into online learning. Therefore, to enhance IoT adoption readiness, it is essential for stakeholders to organize training programs focused on developing digital skills and technological understanding for farmers.

3.4 Practical implications

Based on the findings of this study, several practical implications should be urgently addressed by livestock farmers, government authorities, and relevant stakeholders to enhance the readiness for IoT technology adoption in the smallholder livestock sector.

First, improving farmers' knowledge and capacity regarding IoT must be prioritized. This can be achieved through integrated training programs, workshops, and hands-on mentoring that clearly explain the benefits, operational mechanisms, and practical applications of IoT in farm management [37,38]. Local governments and agricultural extension agencies can collaborate with universities or agritech startups to deliver educational materials that are accessible, easy to understand, and tailored to local needs [39].

Second, although the factors of cost and technological access were not statistically significant in the current model, improving digital infrastructure—such as expanding rural internet connectivity and ensuring the availability of affordable IoT devices—remains crucial to eliminating field-level barriers [40,14]. Consequently, government-led incentive policies, including subsidies for IoT devices, tax incentives for agricultural technology, and micro-financing schemes for smallholder farmers, should be implemented more broadly [41,42].

Institutional support in the form of regulatory frameworks and a collaborative ecosystem involving industry players, academia, and farming communities will significantly accelerate the sustainable and inclusive adoption of digital technologies in the smallholder livestock sector [42].

4 Conclusion

In conclusion, this study reveals that among various external factors, farmers' knowledge of IoT and their attitudes toward new technologies are the most significant determinants influencing their readiness to adopt IoT in the broiler farming sector of Greater Malang. While economic constraints and access to infrastructure did not show a statistically significant impact, the findings underscore the pivotal role of cognitive and psychological preparedness over physical or financial barriers. To address the adoption gap, practical solutions such as targeted training programs, digital literacy enhancement, and community-based knowledge sharing are essential. It is also recommended that policymakers strengthen digital infrastructure and offer financial incentives to support adoption. Future research should explore additional socio-cultural and institutional factors that may affect

IoT adoption across different agricultural contexts in Indonesia, to develop a more holistic and inclusive framework for digital transformation in the livestock sector.

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