International Journal of Sustainability in Research (IJSR)
Vol. 4, No. 3, 2026 : 165-182

Integrating Mixed Methods and Big Data Analytics in Digital Farming to Improve Corn Agribusiness Performance in Bima Regency, Indonesia

Arissaryadin[1]*, Agustia Dwi Pamujiati[2], Reksa Nanda Prayoga[3]
[1,2,3]Faculty of Agriculture, Kadiri University, Kediri
Corresponding Author: Arissaryadin ariessaryadin@unik-kediri.ac.id

A R T I C L E I N F O

Keywords: Digital farming, Big Data Analytics, Mixed Methods, Corn Agribusiness, Digital literacy

Received : 21, March
Revised : 23, April
Accepted: 25, May

A B S T R A C T

This study aims to examine the integration of mixed methods and big data analytics in digital farming for corn agribusiness in Bima Regency as a methodological contribution to strengthening data-driven agribusiness systems. A sequential explanatory mixed methods design was employed, involving 140 farmers as respondents during the period from December 2025 to April 2026. Data were collected through structured surveys, in-depth interviews, and focus group discussions. The variables analyzed included technology adoption, digital literacy, market access, and agribusiness performance. The findings indicate that digital farming has a significant positive effect on agribusiness performance, with digital literacy emerging as the most influential factor. However, limited access to digital markets remains a major constraint. The study highlights the importance of strengthening digital literacy and developing integrated data-based marketing systems to enhance farmers' welfare.

DOI: https://doi.org/10.59890/ijsr.v4i3.428
ISSN-E: 3025-7379
https://dmimultitechpublisher.my.id/index.php/ijsr

INTRODUCTION

Agriculture remains a fundamental pillar of Indonesia's economy, playing a crucial role in ensuring food security and sustaining rural livelihoods. Among strategic commodities, corn holds a significant position, not only for direct consumption but also as a key input for the livestock feed industry. Nationally, the development of corn agribusiness has shown considerable progress in terms of productivity and efficiency; however, structural challenges persist, particularly in value chain governance, price stability, and market integration (Abriani et al., 2022; Montjou et al., 2024; Rahman et al., 2023; Suryanto & Purnomo, 2022).

In eastern Indonesia, particularly in Bima Regency, corn production represents a dominant economic activity and a primary source of rural income. Recent data from Badan Pusat Statistik indicate that corn production in Bima Regency reached approximately 724,000 tons in 2023, positioning it as one of the leading production centers in West Nusa Tenggara (BPS, 2024). Despite this high level of output, improvements in farmers' welfare remain limited. This condition reflects persistent structural inefficiencies, especially in distribution systems and market access, where price volatility during peak harvest periods continues to disadvantage farmers (Hasanah et al., 2025; Putri et al., 2025; Wulandari, 2023).Empirical evidence further indicates that agribusiness performance in Bima is shaped not only by production factors but also by structural and institutional constraints, including limited market access (Putri et al., 2025; Wulandari, 2023) and uneven adoption of innovation (Arissaryadin et al., 2023). These findings suggest that agribusiness challenges are systemic, requiring integrated solutions that extend beyond production oriented approaches.

At the global level, agriculture is undergoing rapid transformation driven by digital technologies. Digital farming integrates tools such as the Internet of Things (IoT), big data analytics, and data-driven decision systems to enhance efficiency, precision, and adaptability (Abiri et al., 2023; Addison et al., 2024; Fielke et al., 2020; Friha et al., 2021; Himesh et al., 2018; Sharma et al., 2024; Silva et al., 2025).

In the context of corn agribusiness, innovations such as artificial intelligence, drones, and biotechnology have demonstrated strong potential to improve productivity and optimize resource utilization (Chaux et al., 2021; Fielke et al., 2020; Friha et al., 2021; Himesh et al., 2018; Ren et al., 2020; Rezvani et al., 2020; Sharma et al., 2024; Silva et al., 2025). However, the effectiveness of these technologies depends largely on farmers' ability to adopt and utilize them within their operational systems.

Despite these advancements, significant gaps remain in the implementation of digital farming, particularly in developing regions. Limited digital literacy, restricted access to market information, and inadequate infrastructure continue to constrain the effectiveness of technological innovation (Arissaryadin et al., 2023; Banunaek et al., 2022; Javandira et al., 2024; Suryanto & Purnomo, 2022; Yusriadin et al., 2024). Moreover, prior studies indicate that data driven approaches often fail to produce optimal outcomes when they are not aligned with farmers socioeconomic contexts (Himesh et al., 2018; Ren et al., 2020; Sharma et al., 2024; Silva et al., 2025).

From an academic perspective, existing research remains fragmented, with data-driven studies focusing primarily on technical modeling, while socioeconomic studies emphasize behavioral and institutional aspects without integrating large scale analytics. Addressing this gap, the present study introduces a novel integrative approach by combining mixed methods and big data analytics within digital farming. This study aims to examine how such integration influences corn agribusiness performance in Bima Regency, identify key determinants, and formulate strategic directions for developing a more effective, context sensitive, and sustainable digital agribusiness system.

LITERATURE REVIEW

Digital Farming and Agribusiness Transformation

The advancement of digital farming has fundamentally transformed agricultural management from conventional practices into integrated, data driven systems. Technologies such as sensors, satellite imagery, artificial intelligence, and digital platforms enable more efficient, precise, and adaptive production processes. In the agribusiness context, this transformation extends beyond cultivation by strengthening value chain integration from upstream production to downstream marketing systems (Abiri et al., 2023; Addison et al., 2024; Sharma et al., 2024; Silva et al., 2025).

Empirical evidence indicates that digital technologies improve efficiency, support better decision-making, and contribute to more adaptive farming systems. However, in developing countries, including Indonesia, the adoption of digital farming remains constrained by structural limitations such as inadequate infrastructure, limited institutional support, and low human resource capacity (Arissaryadin et al., 2023; Suryanto & Purnomo, 2022; Yusriadin et al., 2024).

In the specific context of corn agribusiness, digital transformation cannot be separated from broader systemic challenges. Studies show that agribusiness performance is influenced not only by technological adoption but also by structural and institutional factors such as value chain governance, market access, and farmer capacity (Abriani et al., 2022; Montjou et al., 2024; Rahman et al., 2023; Suryanto & Purnomo, 2022).

Big Data Analytics in Agricultural Systems

Big data analytics plays a critical role in modern agricultural systems by enabling the processing of large-scale and heterogeneous datasets derived from soil conditions, climate variability, and market dynamics. These data-driven approaches improve efficiency, enhance resource optimization, and strengthen decision-making processes within digital farming systems (Abiri et al., 2023; Friha et al., 2021; Sharma et al., 2024; Silva et al., 2025).

Nevertheless, the effectiveness of big data analytics is highly dependent on users' ability to interpret and apply analytical outputs in real world contexts. Evidence suggests that technological sophistication alone is insufficient when it is not aligned with farmers' socioeconomic conditions and capacities (Himesh et al., 2018; Sharma et al., 2024). In Indonesia, particularly in corn agribusiness systems, the adoption of advanced technologies such as artificial intelligence, drones, and biotechnology still faces significant barriers related to knowledge gaps, uneven access, and limited digital literacy (Arissaryadin et al., 2023; Javandira et al., 2024; Yusriadin et al., 2024).

Corn Agribusiness System in Indonesia

Corn agribusiness represents a complex and interdependent system involving production, postharvest handling, distribution, and marketing subsystems. Disruptions in any component can significantly affect overall system performance. In Indonesia, corn is a strategic commodity with a crucial role in food security and the livestock feed industry; however, persistent challenges remain, particularly in value chain governance, price stability, and market integration (Abriani et al., 2022; Montjou et al., 2024; Rahman et al., 2023; Suryanto & Purnomo, 2022).

In regions such as Bima Regency, where corn production is relatively high, these challenges become more pronounced during peak harvest periods. High production levels are often not accompanied by proportional improvements in farmer welfare due to structural inefficiencies in distribution systems and market access (Hasanah et al., 2025; Putri et al., 2025; Wulandari, 2023).

Furthermore, empirical evidence highlights that weak institutional arrangements, limited access to real time market information, and inadequate digital integration contribute to suboptimal agribusiness performance. These constraints are closely linked to broader systemic issues, including limited innovation adoption and structural barriers within rural economies (Arissaryadin et al., 2023; Putri et al., 2025; Wulandari, 2023).

Mixed Methods Approach in Agribusiness Research

The mixed methods approach has gained increasing attention in agribusiness research due to its ability to integrate quantitative rigor with qualitative depth. Quantitative methods allow for objective testing of relationships among variables, while qualitative approaches provide deeper insights into social context, behavioral dynamics, and institutional factors (Makateng et al., 2025). The integration of these approaches enhances both the validity and comprehensiveness of research findings (Creswell & Clark, 2017).

In complex systems such as agribusiness, where technological, social, and economic dimensions interact dynamically, mixed methods research is particularly effective. Recent studies confirm that combining statistical modeling with qualitative insights enables a more holistic understanding of agricultural transformation processes (Brinken et al., 2025; Noori et al., 2024; Tennhardt et al., 2025).

Technology Adoption and Digital Divide

Technology adoption in agriculture is influenced by both individual and systemic factors. The Technology Acceptance Model (TAM), developed by Fred Davis, emphasizes perceived usefulness and ease of use as key determinants of technology acceptance (Matias, 2021; Rahmaningtyas & Kusumawardani, 2025; Song et al., 2021). Meanwhile, the diffusion of innovation theory proposed by

Everett Rogers highlights the role of communication channels and social networks in facilitating adoption processes (Chen & Li, 2022; Long et al., 2014).

Despite these theoretical frameworks, empirical evidence shows that technology adoption in agriculture is often uneven, leading to a persistent digital divide among farmers. Differences in access to information, digital skills, and technological infrastructure contribute to widening economic disparities (Martini & Sgambato, 2025; Zhang et al., 2025; Zhao et al., 2025). In Indonesia, the role of agricultural extension services is also critical in bridging this gap, particularly in enhancing farmers' capacity to adopt digital innovations (Febriansyah et al., 2026; Parinding et al., 2025; Pasambuna et al., 2025).

Conceptual Model of the Study

The conceptual model of this study is developed to explain the relationship between digital farming, big data analytics, and the performance of corn agribusiness within an integrated system framework. Agribusiness performance is positioned as the dependent variable, reflecting outcomes such as productivity, efficiency, and farmers' income. This performance is influenced by three key independent variables: technology adoption, digital literacy, and market access.

Technology adoption refers to the extent to which farmers utilize digital tools and platforms in their farming activities. Digital literacy represents farmers' ability to understand, interpret, and effectively use digital technologies, making it a critical enabling factor. Market access reflects farmers' ability to obtain accurate price information and connect with broader and more efficient distribution channels. These variables operate within the digital farming ecosystem, where big data analytics enhances decision-making processes through data driven insights.

The model further assumes that digital literacy plays a central and mediating role in strengthening the effects of technology adoption and improving access to digital markets. In this context, farmers with higher digital literacy are more likely to adopt technology effectively and benefit from improved market integration. To capture both statistical relationships and contextual dynamics, this study employs a mixed methods approach, integrating quantitative analysis with qualitative insights. This integration allows for a comprehensive understanding of how technological, human, and market factors interact to influence agribusiness performance. Ultimately, the model highlights that sustainable agribusiness development requires not only technological advancement but also strengthened human capacity and inclusive market systems.

Research Hypotheses

Based on the conceptual model and supported by empirical evidence, this study proposes three main hypotheses. First, technology adoption is expected to have a positive and significant effect on the performance of corn agribusiness, as the use of digital tools can enhance efficiency and decision-making processes. Second, digital literacy is hypothesized to exert a positive and significant influence on agribusiness performance and to function as the most dominant factor, given its critical role in enabling farmers to effectively utilize technological innovations. Third, market access is also anticipated to have a positive and significant effect on agribusiness performance, as improved access to market information and distribution channels can strengthen farmers' bargaining positions and optimize economic outcomes.

METHODOLOGY

Research Design

This study employed a mixed methods approach using a sequential explanatory design, in which quantitative analysis was conducted in the first phase, followed by qualitative inquiry to deepen and contextualize the findings. This design was selected to align with the conceptual model, which integrates measurable relationships among variables technology adoption (X1), digital literacy (X2), and market access (X3), with contextual realities influencing agribusiness performance (Y). The integration of both approaches enables a more comprehensive understanding of complex agribusiness systems (Creswell & Clark, 2017; McKim, 2015; Shannon-Baker, 2016).

Research Site and Period

The research was conducted in Bima Regency, Indonesia, a major corn producing region characterized by high production levels alongside persistent challenges in market access and distribution systems. The site was purposively selected to reflect the empirical context of digital farming implementation in developing agribusiness systems. The study was carried out from December 2025 to April 2026, covering preparation, data collection, analysis, and reporting stages.

Population and Sampling

The study population consisted of actors involved in corn agribusiness, with a primary focus on farmers as the main unit of analysis. A total of 140 farmers were selected as quantitative respondents using stratified random sampling based on 18 sub-districts as strata. Proportional allocation was applied to ensure representativeness across regions, followed by simple random sampling within each stratum to minimize selection bias.

For the qualitative phase, 10 key informants were selected using a combination of purposive and snowball sampling techniques. Informants were chosen based on their experience in agribusiness activities, involvement in digital farming practices, and knowledge of market systems. This approach ensured both representativeness and depth of information, consistent with qualitative research principles (Creswell & Clark, 2017; Guest, 2013).

Variables and Measurement

The study employs a conceptual model in which agribusiness performance (Y) is positioned as the dependent variable, influenced by three independent variables: technology adoption (X1), digital literacy (X2), and market access (X3). Technology adoption refers to the extent to which farmers utilize digital tools in agricultural activities, digital literacy reflects their capacity to understand and effectively apply digital technologies, and market access denotes their ability to obtain market information and engage with distribution channels.

Each variable was operationalized through multiple indicators and measured using a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). Specifically, technology adoption was measured using 6 items, digital literacy using 8 items, market access using 5 items, and agribusiness performance using 7 items. All measurement indicators were systematically developed and adapted from established literature on digital agriculture, technology adoption, and agribusiness systems to ensure conceptual validity and empirical relevance.

Data Sources and Collection Techniques

This study drew upon both primary and secondary data sources to ensure a comprehensive and triangulated analysis. Primary data were collected through structured questionnaires administered to farmers, complemented by in-depth interviews and focus group discussions (FGDs) to capture richer contextual insights. Secondary data were obtained from government reports, agricultural databases, and digital data platforms relevant to big data analytics in agriculture (Johnson, 2015; Molina-Azorín & Fetters, 2016).

In practice, quantitative data were generated through structured survey instruments, while qualitative data were gathered using semi-structured interviews and FGDs to explore farmers' experiences, perceptions, and institutional dynamics in greater depth (Fetters & Freshwater, 2015).

Quantitative Data Analysis

Quantitative data in this study were analyzed using Jamovi, an open source statistical software that supports advanced, transparent, and reproducible analysis. The analytical process began with descriptive statistics to summarize respondent characteristics and the distribution of research variables, including measures such as mean, standard deviation, and frequency. This initial step provided a general overview of the data structure and ensured that the dataset was suitable for further inferential analysis. Subsequently, instrument testing was conducted to assess the quality of the measurement tools. Item validity was evaluated using Pearson correlation, where each item was considered valid if the correlation coefficient exceeded the critical value (r-count > r-table). Reliability testing was performed using Cronbach's Alpha, with a threshold of $\alpha > 0.70$ indicating satisfactory internal consistency across items.

To ensure the robustness of the regression model, a series of classical assumption tests were carried out. These included normality testing using Shapiro Wilk and residual plots, multicollinearity testing using Variance Inflation Factor (VIF < 10), and heteroscedasticity testing through scatterplot and residual analysis. After confirming that all assumptions were met, multiple linear regression analysis was performed to test the proposed hypotheses, namely the effects of technology adoption (H1), digital literacy (H2), and market access (H3) on agribusiness performance. Statistical significance was determined at the 5% level ($\alpha = 0.05$). Finally, model evaluation was conducted using the coefficient of determination (R^2) to assess the explanatory power of the model, along with t-tests to evaluate the significance of each independent variable in explaining variations in agribusiness performance.

Big Data and Machine Learning Analysis

To complement regression analysis, this study employed a machine learning approach using a random forest algorithm to identify patterns and variable importance within a big data framework (Kamilaris & Prenafeta-Boldú, 2018; Liakos et al., 2018; Pantazi et al., 2016; Rozo-Higuera, 2025). This approach enhances predictive accuracy and provides deeper insights into variable interactions within the digital farming ecosystem.

Qualitative Data Analysis

Qualitative data were analyzed using thematic analysis, involving systematic processes of data reduction, coding, categorization, and interpretation. To integrate findings from both approaches, this study employed triangulation and meta-inference techniques, allowing quantitative results to be explained and validated through qualitative insights (Creswell & Clark, 2017; Sandelowski et al., 2012). This integration strengthened the robustness and interpretive depth of the analysis.

Validity and Trustworthiness

To ensure the rigor and trustworthiness of the study, multiple validation strategies were applied. Quantitative data quality was ensured through validity and reliability testing, while qualitative data were validated using source triangulation, method triangulation, and peer debriefing. Furthermore, the study adhered to criteria of credibility, dependability, and confirmability to enhance research integrity (Creswell & Clark, 2017; Greene, 2006).

Ethical Considerations

Ethical considerations were strictly maintained throughout the research process, including obtaining informed consent from all participants, ensuring data confidentiality, and using data responsibly in accordance with academic research standards.

RESEARCH RESULT

Data Description and Respondent Profile

This study involved 140 corn farmers as quantitative respondents and 10 key informants for qualitative inquiry through indepth interviews and focus group discussions (FGDs). Respondents were selected using stratified random sampling across 18 sub districts in Bima Regency to ensure proportional representation.

Table 1. Characteristics of Respondents (n = 140)

Characteristics	Category	Percentage (%)
Age	20–30 years	15
	31–50 years	55
	>50 years	30
Education Level	Primary Junior High	48
	Senior High School	37
	Higher Education	15
Farming Experience	<5 years	12
	5–10 years	34

	>10 years	54
Digital Literacy	Low	46
	Moderate	38
	High	16

The majority of respondents were aged 31–50 (55%), indicating a productive workforce. However, 85% had only primary to secondary education, and 84% exhibited low to moderate digital literacy. This confirms a structural gap between farming experience and digital capability.

Validity and Reliability Testing

Instrument testing confirmed that all measurement items met validity criteria, with Pearson correlation coefficients exceeding the threshold ($r > 0.30$). Reliability testing using Cronbach's Alpha produced values ranging from 0.79 to 0.87, indicating strong internal consistency.

Table 2. Reliability Test Results

Variable	Cronbach's Alpha	Interpretation
Technology Adoption	0.82	Reliable
Digital Literacy	0.87	Reliable
Market Access	0.79	Reliable
Agribusiness Performance	0.85	Reliable

All variables demonstrated Cronbach's Alpha values above 0.70, indicating satisfactory internal consistency. Therefore, the instrument is considered reliable and suitable for further analysis.

Quantitative Analysis and Hypothesis Testing

Multiple linear regression analysis was employed to examine the influence of technology adoption (X1), digital literacy (X2), and market access (X3) on agribusiness performance (Y). Prior to regression analysis, classical assumption tests including normality, multicollinearity, and heteroscedasticity were conducted, and the results confirmed that the data met all required statistical assumptions.

Table 3. Multiple Linear Regression

Variable	Coefficient (β)	t-value	Sig.
Technology Adoption (X1)	0.312	3.845	0.000
Digital Literacy (X2)	0.428	5.217	0.000
Market Access (X3)	0.267	2.996	0.003
$R^2 = 0.68$			

The regression analysis provides robust empirical support for the proposed conceptual model. First, technology adoption is found to have a positive and statistically significant effect on agribusiness performance ($\beta = 0.312$, $p < 0.001$), indicating that the utilization of digital tools contributes to improvements in efficiency and productivity. Second, digital literacy emerges as the most influential factor ($\beta = 0.428$, $p < 0.001$), confirming the theoretical proposition that human capacity plays a central role in determining the effectiveness of digital farming systems. These findings highlight that the benefits of technological innovation are highly dependent on farmers' ability to understand and apply such technologies in practice.

Furthermore, market access is also shown to have a significant positive effect on agribusiness performance ($\beta = 0.267$, $p = 0.003$), emphasizing the importance of access to reliable market information and efficient distribution channels in enhancing farmers' income. Collectively, the model explains 68% of the variance in agribusiness performance ($R^2 = 0.68$), demonstrating strong explanatory power and supporting the validity of the integrated framework proposed in this study. This result reinforces the argument that agribusiness performance is shaped by the interaction between technological adoption, human capacity, and market connectivity.

The results indicate that all independent variables have a positive and statistically significant effect on agribusiness performance. The model explains 68% of the variance ($R^2 = 0.68$), suggesting strong explanatory power. Among the variables, digital literacy shows the highest coefficient ($\beta = 0.428$), identifying it as the most influential factor in improving agribusiness performance. This finding underscores the critical role of farmers' capacity to understand and utilize digital technologies effectively.

Big Data Analysis and Predictive Modeling

In addition to regression analysis, this study applied a machine learning approach using a random forest model to identify patterns and predictive relationships among variables. The model achieved an overall prediction accuracy of 81%, indicating a high level of reliability.

Table 4. Feature Importance in Random Forest Model

Variable	Contribution (%)
Digital Literacy	34
Technology Adoption	29
Market Access	21
Other Variables	16

The findings from the machine learning model are consistent with the regression results, further confirming that digital literacy is the most influential factor in determining agribusiness performance. This convergence strengthens the robustness of the findings.

Qualitative Findings: Interviews and FGDs

Interviews with 10 key informants reveal that farmers generally acknowledge the importance of digital technologies but face substantial barriers in practical implementation. The most frequently cited constraints include limited technical knowledge, lack of training, and insufficient institutional support. These findings directly explain the low levels of digital literacy identified in the quantitative analysis, supporting the role of digital literacy as a critical enabling variable (H2).

FGD discussions further highlight that traditional marketing systems remain dominant. Farmers continue to rely on intermediaries, resulting in weak bargaining power and limited price transparency. Participants also emphasize the absence of real-time market information, which often leads to suboptimal selling decisions during peak harvest periods. This provides strong qualitative evidence supporting the significance of market access (H3).

Additionally, participants report that although digital platforms are available, their utilization is constrained by poor infrastructure and unstable internet connectivity. This indicates that technological availability alone is insufficient without adequate human capacity and institutional readiness.

Integration of Mixed Methods Findings

The integration of quantitative and qualitative findings reveals a strong convergence of evidence, consistent with the principles of a mixed methods framework. The quantitative analysis confirms statistically significant relationships among the key variables, supporting hypotheses H1 through H3. These results provide empirical validation of the proposed model, indicating that technology adoption, digital literacy, and market access each contribute meaningfully to agribusiness performance.

Complementing these findings, the qualitative evidence offers deeper insights into the mechanisms underlying these relationships. In particular, digital literacy emerges as the central linking variable that enhances the effectiveness of technology adoption while simultaneously facilitating improved market access. This interplay reinforces the conceptual model's assumption that agribusiness performance is not determined by isolated factors, but rather by the dynamic interaction of technological capacity, human capability, and market conditions within an integrated digital farming ecosystem.

Synthesis in Relation to the Conceptual Model

Overall, the findings provide strong empirical support for the proposed conceptual model and underlying theoretical framework. The results indicate that agribusiness performance cannot be explained solely by the extent of technology adoption; rather, it is substantially shaped by farmers' digital literacy and their ability to access and utilize market information effectively. This suggests that technological advancement, while important, must be accompanied by adequate human capacity and institutional support to generate meaningful improvements in agribusiness outcomes.

More specifically, the analysis confirms that technology adoption contributes positively to agribusiness performance (H1), while digital literacy emerges as the most influential determinant (H2). In addition, market access plays a significant complementary role in enhancing performance (H3). Taken together, these findings reinforce the argument that the success of digital farming depends on a holistic integration of technological tools, human competencies, and efficient market systems, as consistently highlighted in the existing literature.

DISCUSSION

The findings of this study provide strong empirical support for the conceptual model, demonstrating that agribusiness performance is significantly influenced by the interaction of technology adoption, digital literacy, and market access within a digital farming system. The results confirm all proposed hypotheses (H1–H3), with digital literacy emerging as the most dominant determinant. This indicates that the effectiveness of digital farming is not primarily driven by the availability of technology, but rather by farmers' capacity to understand, interpret, and utilize digital tools effectively (Himesh et al., 2018).

The significant effect of technology adoption on agribusiness performance (H1) is consistent with prior studies highlighting the role of digital technologies in improving agricultural efficiency and productivity. Digital farming systems based on big data analytics and precision agriculture have been shown to enhance decision making processes and optimize resource utilization (Abiri et al., 2023; Friha et al., 2021; Sharma et al., 2024; Silva et al., 2025). In the context of agribusiness, technological integration also strengthens value chain coordination from production to marketing systems (Addison et al., 2024). However, the present study refines these findings by demonstrating that technology adoption alone is insufficient without adequate user capability (Arissaryadin et al., 2023).

The dominance of digital literacy (H2) represents a critical contribution to the literature. This finding reinforces the argument that technological sophistication must be aligned with users' capacities and socioeconomic conditions. Empirical evidence shows that the effectiveness of digital farming is highly dependent on farmers' ability to interpret and utilize digital information (Himesh et al., 2018; Sharma et al., 2024). Furthermore, this result reflects the persistent digital divide in agricultural systems, where unequal access to knowledge and digital skills limits the benefits of innovation, particularly in developing countries (Yusriadin et al., 2024).

Furthermore, the significant role of market access (H3) confirms that agribusiness performance is strongly linked to the efficiency of distribution systems and access to market information. Structural inefficiencies in value chain governance, price stability, and market integration have been widely identified as major constraints in corn agribusiness systems (Abriani et al., 2022; Montjou et al., 2024; Rahman et al., 2023; Suryanto & Purnomo, 2022). In regional contexts such as Bima Regency, these challenges are more pronounced, particularly during peak harvest periods when high production is not accompanied by proportional improvements in farmer welfare (Hasanah et al., 2025; Putri et al., 2025; Wulandari, 2023). The findings of this study strengthen this argument by demonstrating that limited digital market access contributes directly to price volatility and weak bargaining positions among farmers.

From a systems perspective, the findings reveal that the primary bottleneck in corn agribusiness is not production capacity, but rather the imbalance between production and market subsystems. Agribusiness should therefore be understood as an integrated system in which disruptions in one component, particularly distribution and market access, can significantly affect overall performance (Abriani et al., 2022; Rahman et al., 2023). This systemic perspective also aligns with evidence showing that agribusiness performance is shaped by the interaction of technological, institutional, and structural factors rather than production variables alone (Montjou et al., 2024; Suryanto & Purnomo, 2022).

Methodologically, this study addresses a significant gap identified in previous research, where data driven approaches and socioeconomic analyses are often treated separately. By integrating quantitative and qualitative approaches, this study provides a more comprehensive understanding of agribusiness systems. Mixed methods research enables the combination of statistical rigor with contextual insights, thereby enhancing the validity and depth of analysis (Brinken et al., 2025; Makateng et al., 2025; Noori et al., 2024; Tennhardt et al., 2025). This approach is particularly relevant in complex systems such as digital agribusiness, where technological, human, and institutional dimensions interact dynamically.

Overall, the findings confirm that sustainable improvements in agribusiness performance require a balanced integration of technology, human capacity, and market systems. Digital farming, supported by big data analytics, has the potential to transform agricultural systems into more efficient and adaptive structures; however, its success depends fundamentally on digital literacy and inclusive market access (Abiri et al., 2023; Silva et al., 2025; Yusriadin et al., 2024). Without strengthening these enabling factors, technological advancements alone will not be sufficient to achieve sustainable agribusiness development.

CONCLUSIONS AND RECOMMENDATIONS

This study demonstrates that the integration of mixed methods and big data analytics significantly improves corn agribusiness performance. Digital literacy emerges as the most influential factor, followed by technology adoption and market access. The findings further indicate that the primary constraint lies in market systems rather than production. Therefore, increasing output alone is insufficient without strengthening distribution and market integration.

Strategically, improving digital literacy should become a priority. In addition, developing integrated digital marketing systems is essential to enhance price transparency and market access. Policymakers should focus on building an inclusive digital ecosystem through infrastructure development, training programs, and institutional support to ensure sustainable transformation.

ADVANCED RESEARCH

Despite its contributions, this study is limited by its focus on a single regional context and the use of partially aggregated data. Future research should expand the geographical scope and incorporate real time data from IoT based systems to enhance analytical precision. Additionally, the application of advanced predictive models, such as artificial intelligence and deep learning, is recommended to further explore dynamic interactions within agribusiness systems. Greater attention should also be given to policy and institutional dimensions to better understand their role in accelerating sustainable digital transformation in agriculture.

ACKNOWLEDGMENT

The author gratefully acknowledges Widi Artini, Dean of the Faculty of Agriculture at Universitas Kadiri, for her valuable support and constructive suggestions throughout the implementation of this research. Her guidance has significantly contributed to the completion and quality of this study.

REFERENCES

Abiri, R., Rizan, N., Balasundram, S. K., Shahbazi, A. B., & Abdul-Hamid, H. (2023). Application of digital technologies for ensuring agricultural productivity. Heliyon, 9, e22601. https://doi.org/10.1016/j.heliyon.2023.e22601

Abriani, D. M., Lestari, D., & Rosanti, N. (2022). Keberhasilan sistem agribisnis jagung pada korporasi petani di Desa Marga Catur Kecamatan Kalianda Kabupaten Lampung Selatan. Jurnal Ekonomi Pertanian dan Agribisnis, 6(2), 463–477. https://doi.org/10.21776/ub.jepa.2022.006.02.12

Addison, M., Bonuedi, I., Arhin, A. A., Wadei, B., Owusu-Addo, E., Fredua Antoh, E., & Mensah-Odum, N. (2024). Exploring the impact of agricultural digitalization on smallholder farmers' livelihoods in Ghana. Heliyon, 10, e27541. https://doi.org/10.1016/j.heliyon.2024.e27541

Arissaryadin, A., Yuliati, Y., Hidayat, K., & Dwi Cahyono, E. D. (2022). A questionnaire to determine the work motivation of agricultural extension workers in Indonesia. Agricultural Socio-Economics Journal, 22(2), 103–109. https://doi.org/10.21776/ub.agrise.2022.022.2.4

Banunaek, M. F., Muhammad, E. V., Mahardika, C. B., Abineno, J. C., Puay, Y., & Pobas, M. (2022). Pengaruh psikologi petani terhadap penerapan inovasi teknologi fermentasi jagung Bose pada Gapoktan Setetes Madu Fatuleu Desa Camplong II, Kabupaten Kupang. Jurnal Penyuluhan, 18(2), 336–346. https://doi.org/10.25015/18202241060

Brinken, J., Trojahn, S., & Behrendt, F. (2025). A mixed method approach to integrate digitization and sustainability on German farms. Smart Agricultural Technology, 11, 101012.

Badan Pusat Statistik. (2024). Produksi jagung Kabupaten Bima tahun 2023. Badan Pusat Statistik.

Chen, X., & Li, T. (2022). Diffusion of agricultural technology innovation: Research progress of innovation diffusion in Chinese agricultural science and technology parks. Sustainability, 14(22), 15008. https://doi.org/10.3390/su142215008

Chaux, J. D., Sanchez-Londono, D., & Barbieri, G. (2021). A digital twin architecture to optimize productivity within controlled environment agriculture. Applied Sciences, 11(19), 8875. https://doi.org/10.3390/app11198875

Creswell, J. W. (2014). Research design: Qualitative, quantitative, and mixed methods approaches (4th ed.). Sage Publications.

Creswell, J. W., & Clark, V. L. P. (2017). Designing and conducting mixed methods research (3rd ed.). Sage Publications.

Febriansyah, M., Taufik, Y., & Salahuddin, S. (2026). Peran penyuluh pertanian dalam meningkatkan kapasitas petani padi sawah di Kelurahan Baruga Kecamatan Baruga Kota Kendari. JIIKPP (Jurnal Ilmiah Inovasi dan Komunikasi Pembangunan Pertanian), 5(2), 208–219. https://doi.org/10.56189/jiikpp.v5i2.49

Fetters, M. D., & Freshwater, D. (2015). Publishing a methodological mixed methods research article. Journal of Mixed Methods Research, 9(3), 203–213.

Fielke, S., Taylor, B., & Jakku, E. (2020). Digitalisation of agricultural knowledge and advice networks: A state-of-the-art review. Agricultural Systems, 180, 102763. https://doi.org/10.1016/j.agsy.2019.102763

Friha, O., Ferrag, M. A., Shu, L., Maglaras, L., & Wang, X. (2021). Internet of Things for the future of smart agriculture: A comprehensive survey of emerging technologies. IEEE/CAA Journal of Automatica Sinica, 8(4), 718–752. https://doi.org/10.1109/JAS.2021.1003925

Greene, J. C. (2006). Toward a methodology of mixed methods social inquiry. Research in the Schools, 13(1), 93–98.

Guest, G. (2013). Describing mixed methods research: An alternative to typologies. Journal of Mixed Methods Research, 7(2), 141–151. https://doi.org/10.1177/1558689812461179

Hasanah, L., Fauziyah, E., & Suprapti, I. (2025). Efisiensi teknis dan faktor penentu inefisiensi pada usahatani jagung di Pamekasan Indonesia. JIA (Jurnal Ilmiah Agribisnis): Jurnal Agribisnis dan Ilmu Sosial Ekonomi Pertanian, 10(2), 166–176. https://doi.org/10.37149/jia.v10i2.1839

Himesh, S., Rao, E. V. S. P., Gouda, K. C., Ramesh, K. V., Rakesh, V., Mohapatra, G. N., Rao, B. K., Sahoo, S. K., & Ajilesh, P. (2018). Digital revolution and big data: A new revolution in agriculture. CABI Reviews, 1–7.

Javandira, C., Widyastuti, L. P. Y., & Ananda, K. D. (2024). Pengembangan potensi petani jagung melalui edukasi budidaya jagung hibrida di Desa Kesiut, Kabupaten Tabanan, Bali. Nusantara Community Empowerment Review, 2(2), 90–95.

Johnson, J. S. (2015). Broadening the application of mixed methods in sales research. Journal of Personal Selling & Sales Management, 35(4), 334–345. https://doi.org/10.1080/08853134.2015.1091687

Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. Computers and Electronics in Agriculture, 147, 70–90. https://doi.org/10.1016/j.compag.2018.02.016

Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. Sensors, 18(8), 2674. https://doi.org/10.3390/s18082674

Long, D., Li, T., & Yu, Z. (2014). Research on behavior of farmers' adoption under technology diffusion of agriculture: Abroad progress and domestic trends. Areal Research and Development, 33, 132–139.

Makateng, D., & Mokala, N. (2025). Understanding qualitative research methodology: A systematic review. E-Journal of Humanities, Arts and Social Sciences, 6, 327–335. https://doi.org/10.38159/ehass.2025637

Martini, E., & Sgambato, M. C. (2025). Digital inequalities and access to technology: Analyzing how digital tools exacerbate or mitigate social inequalities. Societies, 15(11), 318. https://doi.org/10.3390/soc15110318

Matias, J. B. (2021). Understanding intention and behavior toward online purchases of agricultural and fisheries products using the extended technology acceptance model. International Journal of Enterprise Information Systems, 17(4), 118–137. https://doi.org/10.4018/IJEIS.2021100107

McKim, C. A. (2015). The value of mixed methods research: A mixed methods study. Journal of Mixed Methods Research, 11(2), 202–222. https://doi.org/10.1177/1558689815607096

Molina-Azorín, J. F., & Fetters, M. D. (2016). Mixed methods research prevalence studies: Field-specific studies on the state of the art of mixed methods research. Journal of Mixed Methods Research, 10(1), 52–68. https://doi.org/10.1177/1558689815580592

Montjou, R. Y., Christoporus, & Sirappa, E. (2024). Analisis faktor-faktor yang memengaruhi produksi usahatani jagung di Desa Uelene Kecamatan Pamona Selatan Kabupaten Poso. Agrotekbis: Jurnal Ilmu Pertanian (e-Journal), 12(2), 358–367.

Noori, S., Roosta, K., & Naderi, N. (2024). A mixed-method approach to designing an entrepreneurial behavior development model in agricultural cooperatives of Kermanshah Province. Frontiers in Sustainable Food Systems, 8, 1432331. https://doi.org/10.3389/fsufs.2024.1432331

Pantazi, X. E., Moshou, D., Alexandridis, T., Whetton, R. L., & Mouazen, A. M. (2016). Data-driven approaches for precision agriculture: A review. Computers and Electronics in Agriculture, 123, 172–180. https://doi.org/10.1016/j.compag.2016.02.008

Parinding, B., Mahmud, M., & Ibrahim, H. (2025). Optimalisasi peran penyuluh pertanian dalam pengembangan kapasitas petani di Tana Toraja. Journal of Agribusiness Science and Rural Development, 5(1), 17–32.

Pasambuna, H., Pobela, E., & Paputungan, N. (2025). Analisis peranan penyuluh pertanian untuk meningkatkan kinerja usaha tani padi sawah di Kecamatan Kotamobagu Timur. Jurnal Literasi Ekologi dan Sains Alam, 1(2), 41–53.

Putri, R., Sjah, T., & Budastra, K. (2025). Pengembangan model agribisnis berkelanjutan pada tanaman jagung sebagai komoditas unggulan pertanian. Jurnal Economina, 4(11).

Rahman, T., Sari, N., & Santoso, R. (2023). Kemitraan industri dan peningkatan pendapatan petani jagung di Sulawesi Selatan. Jurnal Agribisnis Indonesia, 12(1), 45–56.

Rahmaningtyas, A., & Kusumawardani, A. (2025). Technology acceptance model (TAM) and perceived risk in online purchase decisions for traditional foods, Indonesia. Jurnal Ilmiah Membangun Desa dan Pertanian, 10(5), 544–555. https://doi.org/10.37149/jimdp.v10i5.2320

Ren, G., Lin, T., Ying, Y., Chowdhary, G., & Ting, K. C. (2020). Agricultural robotics research applicable to poultry production: A review. Computers and Electronics in Agriculture, 169, 105216. https://doi.org/10.1016/j.compag.2020.105216

Rozo-Higuera, C. (2025). A mixed-method approach for domain analysis in interdisciplinary fields using bibliometrics: The case of global studies. Information, 16(4), 304. https://doi.org/10.3390/info16040304

Sandelowski, M., Voils, C. I., Leeman, J., & Crandell, J. L. (2012). Mapping the mixed methods–mixed research synthesis terrain. Journal of Mixed Methods Research, 6(4), 317–331. https://doi.org/10.1177/1558689811427913

Shannon-Baker, P. (2016). Making paradigms meaningful in mixed methods research. Journal of Mixed Methods Research, 10(4), 319–334. https://doi.org/10.1177/1558689815575861

Sharma, A., Prakash, A., Bhambota, S., & Kumar, S. (2024). Investigations of precision agriculture technologies with application to developing countries. Environment, Development and Sustainability.

Silva, B. C. d., Prado, R. d. M., Campos, C. N. S., Baio, F. H. R., Teodoro, L. P. R., Teodoro, P. E., & Santana, D. C. (2025). Applicability of technological tools for digital agriculture with a focus on estimating the nutritional status of plants. AgriEngineering, 7(5), 161. https://doi.org/10.3390/agriengineering7050161

Song, H. J., Ruan, W. J., & Jeon, Y. J. J. (2021). An integrated approach to the purchase decision-making process of food-delivery apps: Focusing on the TAM and AIDA models. International Journal of Hospitality Management, 95, 102943. https://doi.org/10.1016/j.ijhm.2021.102943

Suryanto, D., & Purnomo, H. (2022). Peran koperasi dalam stabilisasi harga jagung di Grobogan dan Bojonegoro. Jurnal Agribisnis dan Sosial Ekonomi Pertanian, 10(2), 77–89.

Tennhardt, L. M., Home, R., Yen, N. T. B., et al. (2025). Mixed method evaluation of factors influencing the adoption of organic participatory guarantee system certification among Vietnamese vegetable farmers. Agriculture and Human Values, 42, 885–904. https://doi.org/10.1007/s10460-024-10643-7

Wulandari, R. (2023). Struktur pasar jagung dan distribusi keuntungan petani di NTB. Jurnal Agribisnis Indonesia, 11(1), 12–23.

Yusriadin, Y., Mas'uf, A., Purwanti, R. E., Syarni, P., Padangaran, N. B., Buana, T., & Mardin, M. (2024). Hubungan dan pengaruh motivasi, partisipasi dan adopsi teknologi petani terhadap produktivitas lahan usahatani jagung di Kabupaten Konawe Selatan. Jurnal Ilmiah Penyuluhan dan Pengembangan Masyarakat, 4(4), 352–360. https://doi.org/10.56189/jippm.v4i4.46

Zhang, J., Li, Y., & Fang, Z. (2025). Two digital divides and income inequality: A global perspective. Journal of Applied Economics, 28(1). https://doi.org/10.1080/15140326.2025.2568247

Zhao, L., Ye, J., & Shao, K. (2025). Digital empowerment and economic equity: Exploring the impact of household digital capability on income inequality. Telecommunications Policy, 49(9).