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Business Intelligence Adoption in Local Agribusiness: Critical Success Factors and Performance Metrics

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Abstract
Business intelligence (BI) is essential for decision-making and competitiveness in many industries, including agribusiness, in the digital age. This study examines the key elements impacting BI adoption in North Sulawesi agricultural businesses. The mixed-methods study uses quantitative data from 276 agribusiness firms (response rate: 78.86%) and qualitative insights from 12 important stakeholders through semi-structured interviews. Technology infrastructure readiness (TIR), organizational readiness and support (ORS), human capital capability (HCC), and external environmental factors (EEF) are the four dimensions of the conceptual framework. Organizational readiness support is the strongest predictor of BI adoption, with a path coefficient of 0.603 and a substantial impact size ($f^2 = 0.782$). Additionally, the model indicates a direct relationship between Organizational readiness and support and Agricultural Process Innovation Performance (APIP) ($\beta = 0.333$). Research indicates that technology infrastructure readiness positively impacts BI adoption ($\beta = 0.168$), emphasizing the significance of strong IT systems. While human capital capability has a minor impact on BI adoption ($\beta = 0.151$), it needs significant organizational support to improve its impact on APIP. External environmental factors have a minor but significant impact ($\beta = 0.119$), indicating market dynamics and regulatory pressures influence BI adoption. The model predicts 77.2% of APIP and 68.2% of BI adoption. These findings add agribusiness-specific features to technology adoption models. The report offers policymakers, technology suppliers, and agricultural managers practical advice on BI deployment to improve sector efficiency and sustainability in emerging nations.

Keywords
Business Intelligence, Agribusiness, Technology Adoption, Digital Transformation, Organizational Readiness, Agricultural Process Innovation Performance

1. Introduction
In digital transformation era , business intelligence (BI) has emerged as a critical technology framework that enables organizations to transform raw data into actionable insights for strategic decision-making (Jiménez-Partearroyo & Medina-López, 2024). In February 2023, Vantage Market Research revealed that the global business intelligence market was valued at USD 23.5 billion in 2021 and is anticipated to reach USD 35.6 billion by 2028, with a compound annual growth rate (CAGR) of 7.2% during the forecast period of 2022-2028. The integration of business intelligence as a solution is becoming essential for maintaining competitiveness and sustainability in a complex market environment, and the agriculture sector is no exception(Bordeleau et al., 2020; Leal, 2024).

The agribusiness sector encounters considerable challenges in today's digital economy, such as market volatility, the effects of climate change, disruptions in supply chains, and shifting consumer preferences (Huyen et al., 2023). According to research by Klingenberg et al. (2022), it is crucial to comprehend alterations in the dimensions of activities, flows, actors, and governance within the framework of digital transformation in this sector (Klingenberg et al., 2022) These challenges are particularly acute in developing regions, where traditional farming practices intersect with emerging technological capabilities (Giller et al., 2021; Khan et al., 2021; Khatri et al., 2024). Agricultural businesses in Indonesia, particularly North Sulawesi, provide 9.85% to the provincial GRDP and employ 55–65% of the workforce (BPS-Statistics North Sulawesi Province, 2024; Loho et al., 2023). Traditional farmers handle almost 95% of exceptional commodities like coconuts, which cover 273,331 hectares (N. Kairupan et al., 2023). The development of this sector is impeded by the fact that only 15-25% of farmers utilized digital technology in 2020 (Loho et al., 2023). Poor rural infrastructure, low farmer digital literacy, and high technology adoption costs are the primary factors contributing to the slow digital transformation(Loho et al., 2023).

Digital technologies, especially Business Intelligence, boost agricultural output, yet many smallholder farmers have yet to use them (Choruma et al., 2024; Kos & Kloppenburg, 2019). According to Geng et al. (2024), many farmers know digital technology's benefits, but smallholder farmers' inadequate resources hinder them from embracing it (Geng et al., 2024). Sanabia-Lizarraga et al. (2024) highlighted that social and economic issues often inhibit smallholder farmers from embracing this technology, since many feel alienated from digitalization due to a lack of help to grasp and execute new technologies (Sanabia-lizarraga et al., 2024). Gabriel and Gandorfer (2023) showed that many smallholder farmers are still unwilling to utilize digital technologies due to a lack of understanding and cash (Gabriel & Gandorfer, 2023). Dewry et al. (2019) observed that larger farms with more investment resources employ digital technologies more (Drewry et al., 2019). Digitalization has several benefits however Smidt and Jokonya (2022) and Abdulai et al. (2023) observes that smallholder farmers often lack the knowledge and skills to apply it (Abdulai et al., 2023; Smidt & Jokonya, 2022). Digital technologies can improve production monitoring and management (Ciruela-Lorenzo et al., 2020; Fuentes-Peñailillo et al., 2024), however Rijswijk et al. (2023) claims smallholder farmers fear danger and unpredictability (Rijswijk et al., 2023). Finally, Abdulai (2022) and Fabregas et al. (2019) discovered that smallholder farmers need education and finance to employ digital technology daily (Abdulai, 2022; Fabregas et al., 2019).

Prior research has thoroughly investigated BI adoption across different sectors, with studies conducted by Bany Mohammad et al. (2022) and Bordeleau et al. (2020) highlighting essential success factors in both manufacturing and service industries (Bany Mohammad et al., 2022; Bordeleau et al., 2020). Nonetheless, these findings may not directly apply to the agribusiness context, especially in developing regions where distinct challenges are present (Pawlak & Kołodziejczak, 2020). The unique features of local agribusinesses, such as seasonal operations, intricate supply chains, and fluctuating product quality, require a tailored framework for the adoption of business intelligence (Gupta et al., 2023). This study aims to examine the key factors that affect the adoption of business intelligence in the local agriculture sector, namely in North Sulawesi. The study examines four essential dimensions: technology infrastructure, organizational readiness, human capital proficiency, and external environmental factors. These characteristics have been chosen because they are supported by preliminary research that emphasizes their significance within the context of the local environment and their compatibility with preexisting frameworks for the dissemination of technology.

The primary objectives of this study are threefold: (1) to identify and validate the critical success factors influencing BI adoption in the local agricultural sector; (2) to develop a comprehensive framework for assessing BI implementation readiness in agricultural organizations; and (3) to establish performance metrics to measure the effectiveness of BI initiatives in the agribusiness context. These objectives are particularly relevant given the Indonesian government’s Digital Agriculture 2024 initiative, which aims to accelerate technology adoption in the agricultural sector.
This study contributes to both theoretical and practical areas. Theoretically, this study extends existing technology adoption models by incorporating context-specific factors relevant to agricultural operations in a developing region (Daraz et al., 2024). This study develops a new framework that takes into account the unique characteristics of local agribusinesses, including seasonal variability, product perishability, and market volatility. The finding will provide important information for policymakers, technology providers, and agricultural experts in the creation and implementation of successful BI solutions.

The importance of this study is underscored by the increasing pressure on agribusinesses to maintain competitiveness, improve operational efficiency, and ensure sustainability in a rapidly evolving digital landscape (Bahn et al., 2021; Tanvi Bhardwaj & Ankit Yadav, 2023). The results will be especially pertinent to regional agricultural development agencies, technological service providers, and educational institutions engaged in capacity building for the agricultural sector. Moreover, the findings of this study will guide policy suggestions to advance digital transformation in the agriculture sector, aligning with national development objectives.

The subsequent sections of this work are organized as follows: Section 2 provides an extensive examination of pertinent literature, concentrating on ideas of BI acceptance and the deployment of agricultural technology. Section 3 delineates the research approach, encompassing data collecting and analytical techniques. Section 4 delineates the findings and analysis, whilst Section 5 explores consequences and offers recommendations. Section 6 ultimately finishes the report by summarizing the principal findings and proposing avenues for future research.

2. Materials and Methods

2.1. Conceptual Framework

This study establishes a framework that comprises four primary dimensions: technology infrastructure readiness (TIR), organizational readiness and support (ORS), human capital capability (HCC), and external environmental factors (EEF). This framework aims to understand the adoption of business intelligence (BI) in the local agribusiness sector, with the goal of enhancing agricultural process innovation performance (APIP).

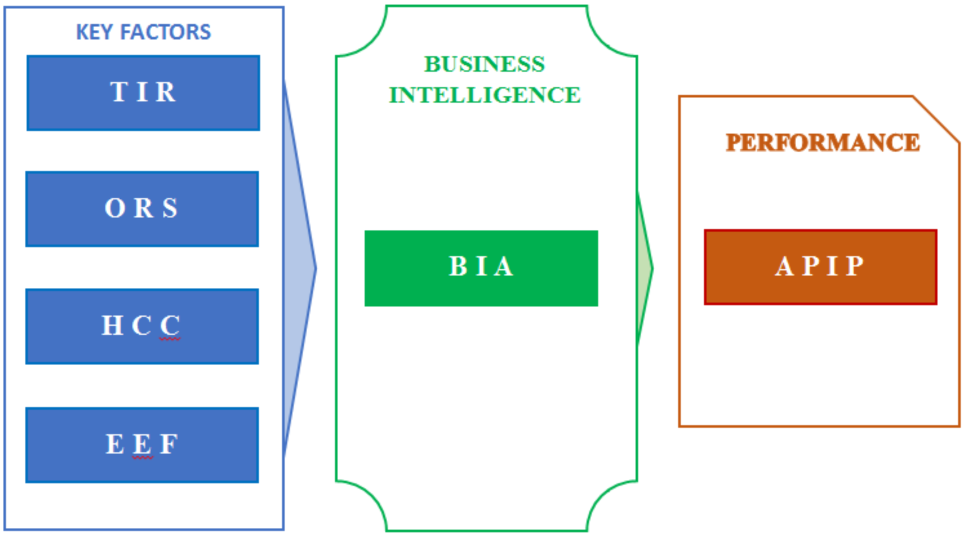

Fig. 1 Conceptual Framework

Figure 1 Shows a conceptual framework designed to provide guidance in identifying critical factors influencing BI adoption in local agribusiness, particularly in North Sulawesi, which faces unique challenges in the digitalization process.

2.2 Research Design

This mixed-methods study examined local agribusinesses' Business Intelligence adoption success variables. The merging of quantitative and qualitative methodologies gave comprehensive insights and methodological triangulation, improving validity and dependability. Quantitative data collection preceded qualitative investigation in the sequential explanatory design of the research framework.

2.3 Data Collection and Sample Selection

The research population consisted of agribusiness enterprises that were located in North Sulawesi, Indonesia. The survey was conducted among 350 agribusinesses, and 288 questionnaires were returned, resulting in a response rate of 82.29%. 276 responses were determined to be legitimate for the final analysis after being screened for accuracy, completeness, and engagement quality, resulting in an effective response rate of 78.86%. This sample size significantly surpasses the minimum threshold for PLS-SEM analysis, which necessitates ten times the maximum number of structural paths directed at any construct in the structural model (Hair et al., 2017).

2.4 Research Instruments

A structured questionnaire was implemented during the quantitative phase to evaluate four critical variables. Six exhaustive items were used to evaluate the Technology Infrastructure Readiness (TIR) construct: IT Infrastructure adequacy for BI implementation, system integration and maintenance capabilities, data quality management system, technical scalability of systems and network connectivity infrastructure. These factors assessed the organizations' technological preparedness and skills.

Organizational Readiness and Support (ORS) was assessed using strategic alignment, resource allocation, innovation culture, change management effectiveness, and cross-functional collaboration. These components were carefully selected to assess the organization's business intelligence (BI) preparedness.

Technical competency and digital literacy, data analytic lities, problem-solving ability, training and development, and knowledge sharing procedures were assessed for Human Capital Capability (HCC) capabilities needed for business intelligence deployment.

Five key indicators were employed to assess External Environment Factors (EEF): market dynamic and competition pressure, customer expectations, regulatory requirements, industry technological trends, and business partner influence. These factors were chosen to conduct a thorough evaluation of the external factors that influence the decision to employ BI.

Each concept was assessed using a five-point Likert scale, with 1 indicating strong disagreement and 5 strong agreements. After expert review and pilot testing with 30 respondents, the questionnaire included revised measurement questions with high reliability coefficients.

A comprehensive set of metrics from recent empirical studies in agricultural innovation research measures Agricultural Process Innovation Performance (APIP). Lin et al. (2020) measures the success of implementing a new or significantly improved agricultural process (APIP1) (Lin et al., 2020), which captures innovation adoption. Khan et al. (2021) Sustainability Approach measures process efficiency improvements (APIP2) (Khan et al., 2021), which assesses operational improvements from innovative techniques. Reardon et al. (2019) measures operational cost reductions caused by process innovation in the cost-effectiveness dimension (APIP3) (Reardon et al., 2019). Zambon et al. (2019) approach evaluates the impact of process innovation on agricultural product quality (APIP4) (Zambon et al., 2019). The final dimension, productivity improvement (APIP5), uses Tomich et al. (2019) and Smith et al. (2019) Farming Systems metrics to measure agricultural yield improvements through innovative techniques (Smith et al., 2019; Tomich et al., 2019)

Table 1 Research Variables

Variable	Indicators	Code	Source/Reference
Technology Infrastructure Readiness (TIR)	IT Infrastructure adequacy for BI implementation	TIR1	Bordeleau et al. (2020)
	System integration and maintaiance capabilities	TIR2	
	Data quality management systems	TIR3	
	Technical scalability of systems	TIR4	
	Network connectivity infrastructure	TIR5	
Organizational Readiness Support (ORS)	Strategic alignment with BI initiatives	ORS1	Bany Mohammad et al. (2022), Bordeleau et al. (2020)
	Resource allocation for BI implementation	ORS2	
	Innovation culture development	ORS3	
	Change management effectiveness	ORS4	
	Cross-functional collaboration	ORS5	
Human Capital Capability (HCC)	Technical competency and digital literacy	HCC1	Abdulai et al. (2023), Smidt and Jokonya (2022)
	Data analytic abilities	HCC2	
	Problem-solving ability	HCC3	
	Training and development programs	HCC4	
	Knowledge sharing procedures	HCC5	
External Environmental Factors (EEF)	Market dynamics and competition pressure	EEF1	Pawlak and Kołodziejczak (2020)
	Customer expectations and demands	EEF2	
	Regulatory requirements compliance	EEF3	
	Industry technological trends	EEF4	
	Business partner influence	EEF5	
Business Intelligence Adoption (BIA)	Regular use of BI tools in decision making	BIA1	Jiménez-Partearroyo and Medina-López (2024), Leal (2024)
	Integration of BI systems in operations	BIA2	
	Utilization of BI analytics for planning	BIA3	
	Process support through BI insights	BIA4	
	Strategic importance of BI tools	BIA5	
Agricultural Process Innovation Performance (APIP)	Implementation success of new agricultural processes	APIP1	Lin et al. (2020)
	Process efficiency improvements	APIP2	Khan et al. (2021)
	Operational cost reductions	APIP3	Reardon et al. (2019)
	Agricultural product quality enhancement	APIP4	Zambon et al. (2019
	Productivity and yield improvements	APIP5	Smith et al. (2019)

2.5 Data Analysis

Within the framework of the quantitative data analysis, the software Smart PLS 4.0 was utilized, and the Partial Least Squares Structural Equation Modeling (PLS-SEM) methodology was considered. This approach was selected because of its capacity to manage complicated models that contain a number of different constructs and interactions, all while requiring only a few assumptions regarding the distribution of the data (Dash & Paul, 2021; Hair et al., 2019). The analysis was carried out using a two-stage methodology. In the first stage, the focus was on evaluating the measurement model. This included analyzing the reliability of the indicator through outer loadings, the dependability of the internal consistency through composite reliability, the convergent validity through AVE, the discriminant validity through HTMT criterion, and the collinearity assessment through voltage intensity function values. In the second stage, the evaluation of the structural model was carried out. This included assessing the significance of path coefficients (β), determining the coefficient of determination (R2), determining the effect size (f2), determining the predictive relevance (Q2), evaluating the model fit (SRMR, NFI), and doing an Importance-Performance Map Analysis (IPMA).

2.6 Non-Response Bias

Based on the findings of Darabont et al. (2018), the non-response bias was evaluated by comparing early and late responders through the use of independent t-tests on important dimensions (Darabont et al., 2018). It appears that there is no need for concern regarding non-response bias in this study, as the findings revealed that there were no significant differences between early and late respondents ($p > 0.05$).

2.7 Hypothesis Statement
Figure 2 illustrates the structural model of this research; hence, grounded in the theoretical framework and this structural model, the hypothesis is articulated as follows:

2.7.1 Direct Effect Hypotheses
H1: Technology Infrastructure Readiness (TIR) positively influences Business Intelligence Adoption (BIA)
H2: Organizational Readiness Support (ORS) positively influences Business Intelligence Adoption (BIA)
H3: Human Capital Capability (HRC) positively influences Business Intelligence Adoption (BIA)
H4: External Environmental Factors (EEF) positively influences Business Intelligence Adoption (BIA)
H5: Business Intelligence Adoption (BIA) positively influences Agricultural Process Innovation Performance (PIM)
H6: Technology Infrastructure Readiness (TIR) positively influences Agricultural Process Innovation Performance (PIM)
H7: Organizational Readiness Support (ORS) positively influences Agricultural Process Innovation Performance (PIM)
H8: Human Capital Capability (HRC) positively influences Agricultural Process Innovation Performance (PIM)
H9: External Environmental Factors (EEF) positively influences Agricultural Process Innovation Performance (PIM)

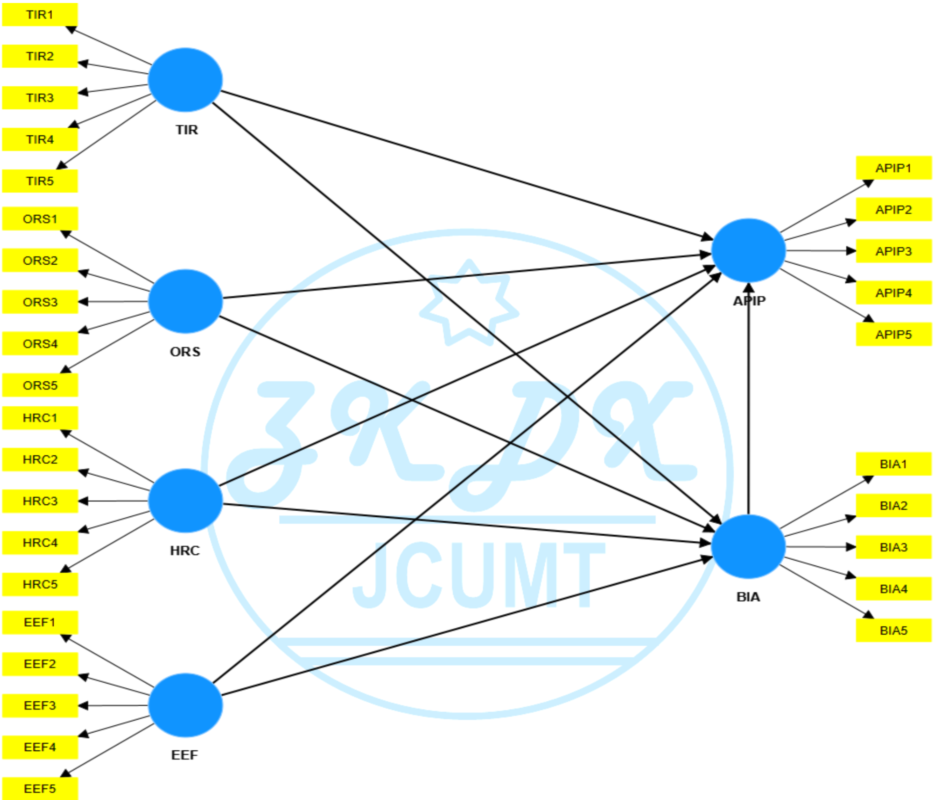

Fig. 2 Structural Model

2.7.2 Mediating Effect Hypotheses
H10: Business Intelligence Adoption (BIA) mediates the relationship between Technology Infrastructure Readiness (TIR) and Agricultural Process Innovation Performance (PIM)
H11: Business Intelligence Adoption (BIA) mediates the relationship between Organizational Readiness Support (ORS) and Agricultural Process Innovation Performance (PIM)
H12: Business Intelligence Adoption (BIA) mediates the relationship between Human Capital Capability (HRC) and Agricultural Process Innovation Performance (PIM)
H13: Business Intelligence Adoption (BIA) mediates the relationship between External Environmental Factors (EEF) and Agricultural Process Innovation Performance (PIM)

2.8 Qualitative Phase
The qualitative phase involved semi-structured interviews with twelve key stakeholders. These stakeholders included agribusiness owners, IT managers, industry experts, and government officials. We used NVivo 12 and systematic theme analysis to analyze interview data. This complementary analysis supported and interpreted quantitative study findings by giving valuable contextual insights.

2.8.1 The Collection of Qualitative Data
Semi-structured interviews were conducted during the data collection process, guided by themes derived from the quantitative analysis. The interview protocol focused on four key areas: external environmental influences, human capital

development strategies, organizational preparation methods, and challenges associated with technology infrastructure implementation. From March to May 2024, we conducted eight in-person sessions at participant offices and four virtual interviews, each lasting 45 to 60 minutes. All interviews were conducted in Indonesian, with English translations provided as needed, and were digitally recorded.

2.8.2 Qualitative Data Analysis

A strategy that was systematic and thematic was utilized for the qualitative analysis, and the software that was used was NVivo 12. First, the recordings of the interviews were transcribed word for word, and then the transcripts were subjected to a comprehensive evaluation of the quality of the translation, followed by participant validation. We used open coding in the first stage of the analysis to identify repeating patterns. The second stage, topic development, involved the aggregation of related codes. The third stage, theme refinement, involved the establishment of precise thematic boundaries. We preserved analytical rigor throughout the process by implementing an audit trail and conducting regular peer debriefing meetings. By adding more data, this qualitative analysis enhanced the quantitative findings and offered important contextual insights.

2.8.3 Quality Assurance and Ethical Considerations

We implemented quality control measures during the research process. The activities encompassed pilot testing of instruments, training for researchers in data collection procedures, and routine validity checks. The research followed rigorous ethical standards, securing institutional review board approval and informed consent from all participants. Secure storage systems and anonymized reporting protocols upheld data confidentiality.

3. Results

3.1 Descriptive Statistics

Tabel 2 Respondents Democraphic Profile

No.	Category	Sub. Category	Percentage	Count
1	Business Size	Medium-sized agribusinesses	62.32%	172
		Small firms	23.19%	64
		Large organizations	14.49%	40
2	Operational Time	5-10 years	45.29%	125
		Over 10 years	32.61%	90
		Less than 5 years	22.10%	61
3	BI Implementation	Early adoption phase	38.41%	106
		Implementation phase	42.03%	116
		Post-implementation phase	19.57%	54

Table 2 Presented the demographic profile of respondents indicated that 62.32% were from medium-sized agribusinesses, 23.19% were from small firms, and 14.49% were from large organizations. Regarding operational time, 45.29% had been in business for 5–10 years; 32.61% for over 10 years; and 22.10% for less than 5 years. Concerning the status of BI implementation, 38.41% were in the early adoption phase, 42.03% in the implementation phase, and 19.57% in the post-implementation phase.

Table 3 Descriptive Statistics of Indicators

Indicators	Mean	Standard deviation	Excess kurtosis	Skewness
BIA1	2.909	0.914	0.202	0.409
BIA2	3.029	0.793	0.519	0.473
BIA3	3.065	0.832	0.053	0.371
BIA4	3.000	0.856	0.177	0.419
BIA5	3.428	0.784	-0.107	0.219
HCC1	3.569	0.722	0.108	-0.126
HCC2	3.199	0.909	-0.236	0.090
HCC3	3.359	0.824	-0.303	0.146
HCC4	3.293	0.858	-0.214	0.087
HCC5	3.257	0.910	-0.356	0.134
TIR1	3.243	0.902	-0.378	-0.023
TIR2	3.054	0.925	-0.315	0.113
TIR3	3.036	0.884	-0.027	0.182
TIR4	2.917	0.883	-0.030	0.354
TIR5	2.779	0.947	-0.095	0.275
EEF1	3.120	0.958	-0.379	0.231
EEF2	3.163	0.932	-0.517	0.210
EEF3	3.120	0.950	-0.407	0.320
EEF4	3.359	0.802	-0.145	0.235

EEF5	2.906	0.958	-0.225	0.438
APIP1	3.250	0.872	0.109	0.217
APIP2	3.409	0.823	-0.103	0.135
APIP3	2.949	0.875	0.724	0.752
APIP4	3.192	0.930	-0.330	0.396
APIP5	3.203	0.865	-0.110	0.404
ORS1	3.022	0.909	-0.149	0.365
ORS2	2.957	0.854	0.267	0.434
ORS3	2.859	0.896	0.189	0.556
ORS4	2.783	0.836	0.840	0.877
ORS5	3.014	0.897	-0.150	0.396
TRS_mean	3.006	0.805	0.181	0.377
ORS_mean	2.927	0.788	0.788	0.851
HCC_mean	3.336	0.746	-0.050	0.265
EEF_mean	3.133	0.819	-0.067	0.534
BIA_mean	3.101	0.732	0.774	0.884
APIP_mean	3.201	0.765	0.641	0.692

Table 3 reveals that all measurement indicators have mean values between 2.779 and 3.569 and standard deviations between 0.722 and 0.958. Data skewness (-0.126 to 0.884) and kurtosis (-0.517 to 0.840) are within the permissible range of ±1.96, indicating a normal distribution. On the other hand, the mean score for External Environmental Factors (EEF) is the highest at 3.133, followed by the mean score for BIA (3.089), TIR (3.006), and ORS (2.927). The fact that all of the constructs have standard deviations that are lower than one thousand demonstrates that the participants' assessments of the measurement indicators are consistent. These findings show that respondents generally concur with the assessed constructs, while maintaining a reasonable level of variability. This lends support to the reliability and validity of the measurement instrument's capacity to capture the desired constructs within the framework of business intelligence adoption.

3.2 Measurement Model Analysis

The measurement model was assessed using multiple criteria: indicator reliability, internal consistency reliability, convergent validity, discriminant validity, and collinearity evaluation.

3.2.1 Indicator Loadings

Table 4 displays the outer loadings for all indicators. All indicators have robust loadings (> 0.70) on their respective structures, indicating high indicator reliability. The loadings vary from 0.841 to 0.897, far exceeding the suggested level.

Table 4 Measurement Model Results: Factor Loadings, Reliability, and Validity Indicators

Variables	Indicators	Loading Factor	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)	VIF
Agricultural Process Innovation Performance (APIP)	APIP1	0.873	0.925	0.925	0.943	0.768	2.779
	APIP2	0.887					3.097
	APIP3	0.883					2.937
	APIP4	0.866					2.722
	APIP5	0.873					2.732
Business Intelligence Adoption (BIA)	BIA1	0.844	0.897	0.898	0.924	0.708	2.296
	BIA2	0.865					2.519
	BIA3	0.861					2.442
	BIA4	0.831					2.178
	BIA5	0.805					2.002
External Environmental Factors (EEF)	EEF1	0.870	0.934	0.936	0.95	0.792	2.809
	EEF2	0.866					2.700
	EEF3	0.912					3.878
	EEF4	0.882					3.011
	EEF5	0.921					4.111
Human Capital Capability (HCC)	HCC1	0.872	0.929	0.932	0.946	0.779	2.863
	HCC2	0.865					2.672
	HCC3	0.885					3.054
	HCC4	0.885					3.074
	HCC5	0.905					3.394
Organizational Readiness Support (ORS)	ORS1	0.876	0.939	0.94	0.954	0.805	2.910
	ORS2	0.902					3.459
	ORS3	0.904					3.548
	ORS4	0.913					3.794
	ORS5	0.890					3.216

Technology Infrastructure Readiness (TIR)	TIR1	0.856	0.932	0.937	0.948	0.785	2.672
	TIR2	0.883					3.050
	TIR3	0.894					3.194
	TIR4	0.901					3.312
	TIR5	0.896					3.183

3.2.2 Internal Consistency Reliability, Convergent Validity and Collinearity Assessment

Table 4 additionally displays the reliability and convergence validity metrics for all constructs. All constructs exhibited exceptional internal consistency and dependability, with Cronbach's alpha and composite reliability (CR) values far exceeding the required threshold of 0.70. CR values varied from 0.924 to 0.954, signifying substantial internal consistency. The Average Variance Extracted (AVE) values for all constructs surpassed the 0.50 barrier, ranging from 0.708 to 0.805, confirming sufficient convergent validity. Furthermore, all VIF values were far below the cautious criterion of 3.3 (range from 2.722 to 3.097), signifying that collinearity was not an issue in the measurement model.

3.2.3 Discriminant Validity Assessment

Table 5 The Heterotrait-Monotrait (HTMT) ratio and the Fornell-Larcker criterion

	Heterotrait-Monotrait (HTMT) ratio						Fornell-Larcker criterion					
Variables	**APIP**	**BIA**	**EEF**	**HC**	**ORS**	**TIR**	**APIP**	**BIA**	**EEF**	**HC**	**ORS**	**TIR**
APIP							**0.876**					
BIA	0.898						0.819	**0.841**				
EEF	0.56	0.522					0.521	0.479	**0.89**			
HCC	0.552	0.487	0.261				0.514	0.445	0.244	**0.883**		
ORS	0.837	0.849	0.468	0.371			0.781	0.780	0.440	0.348	**0.897**	
TIR	0.582	0.561	0.359	0.349	0.455		0.543	0.518	0.339	0.326	0.432	**0.886**

The Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT) ratio are used to assess discriminant validity in Table 5. The square root of Average Variance Extracted (AVE) for each construct (APIP = 0.876, BIA = 0.841, EEF = 0.890, HC = 0.883, ORS = 0.897, and TIR = 0.886) exceeds their inter-construct correlations (ranging from 0.244 to 0.819), confirming discriminant validity. The HTMT ratios provide additional empirical support by being below the conservative threshold of 0.90. These consistent findings across both analytical techniques give strong evidence that each construct is empirically distinct and reflects unique occurrences, a necessity for structural model analysis.

3.3 Structural Model Analysis

This report provides a thorough study of the structural model outcomes, investigating the links across constructs via multiple statistical metrics such as path coefficients, R-squared values, and model fit indices.

Table 6 Path Coefficients and Significance

Structural Path	Path Coefficient (β)	T Statistics	P Values	Significance
BIA -> APIP	0.369	7.354	0.000	***
EEF -> APIP	0.117	3.140	0.001	**
EEF -> BIA	0.119	3.168	0.001	**
HCC -> APIP	0.167	4.929	0.000	***
HCC -> BIA	0.151	3.961	0.000	***
ORS -> APIP	0.333	7.204	0.000	***
ORS -> BIA	0.603	16.740	0.000	***
TIR -> APIP	0.114	3.100	0.001	**
TIR -> BIA	0.168	4.374	0.000	***

The structural model analysis illuminates our study model's construct linkages. Table 6 shows numerous significant route coefficients connections, with ORS being the strongest predictor. Path analysis shows that ORS significantly impacts BIA ($\beta = 0.603$, $t = 16.740$, $p < 0.001$) and APIP ($\beta = 0.333$, $t = 7.204$, $p < 0.001$). Significant path coefficients ($\beta = 0.369$, $t = 7.354$, $p < 0.001$) indicate BIA's mediating involvement.

Table 7 R-Square Values

Construct	R-Square	R-Square Adjusted
APIP	0.772	0.768
BIA	0.682	0.677

The model's predictive capability is evidenced by the R-square values shown in Table 7. The findings demonstrate significant explanatory strength, with R^2 Adjusted values of 0.768 for APIP and 0.677 for BIA, signifying that the model accounts for 76.8% and 67.7% of the variance in these components, respectively. The substantial explained variation indicates that the chosen predictors proficiently encapsulate the primary factors affecting both APIP and BIA.

Table 8 Model Fit Indices

Index	Saturated Model	Estimated Model
SRMR	0.039	0.039
d_ULS	0.703	0.703
d_G	0.418	0.418
Chi-square	666.216	666.216
NFI	0.912	0.912

The model's robustness is evidenced by the R-square values shown in Table 8. The findings Table 3 provides a comprehensive breakdown of the excellent fit indices that demonstrate the resilience of the model. On the other hand, the NFI value of 0.912 is higher than the benchmark value of 0.90, and the SRMR value of 0.039 is significantly lower than the recommended threshold of 0.08. The fact that these fit indices, in conjunction with the Chi-square value of 666.216, give strong evidence for the overall fit of the model with the actual data is a significant accomplishment.

Table 9 f-Square Effect Sizes

Predictor/Outcome	APIP	BIA	EEF	HC	ORS	TIR
APIP	-	-	-	-	-	-
BIA	0.191	-	-	-	-	-
EEF	0.046	0.035	-	-	-	-
HC	0.097	0.060	-	-	-	-
ORS	0.187	0.782	-	-	-	-
TIR	0.040	0.067	-	-	-	-

Note: Effect size interpretation:

- $f^2 \geq 0.35$: Large effect
- $0.15 \leq f^2 < 0.35$: Medium effect
- $0.02 \leq f^2 < 0.15$: Small effect

Table 9 presents effect sizes (f^2) ranging from small to big, with ORS → BIA exhibiting the most substantial effect ($f^2 = 0.782$), succeeded by medium effects for BIA → APIP ($f^2 = 0.191$) and ORS → APIP ($f^2 = 0.187$). The examination of indirect effects reinforces the mediating function of BIA, as all indirect pathways demonstrate statistical significance, especially the ORS → BIA → APIP pathway (0.223, $t = 6.735$, $p < 0.001$). The extensive results presented in Tables 6-8 substantiate the theoretical framework and offer robust empirical evidence for the proposed links in the model.

3.4 Hypothesis Testing Results

Table 10 Direct and Mediation Effects in the Structural Model

Hypothesis	Path	Type	Path Coefficient (β)/Direct Effect ©	Indirect Effect (a×b)	Total Effect	t-value	p-value	Status
H1	ORS → BIA	Direct	0.603			16.740	0.000	Supported
H2	ORS → APIP	Direct	0.333			7.204	0.000	Supported
H3	HC → BIA	Direct	0.151			3.961	0.000	Supported
H4	HC → APIP	Direct	0.167			4.929	0.000	Supported
H5	TIR → BIA	Direct	0.168			4.374	0.000	Supported
H6	TIR → APIP	Direct	0.114			3.100	0.001	Supported
H7	EEF → BIA	Direct	0.119			3.168	0.001	Supported
H8	EEF → APIP	Direct	0.118			3.140	0.001	Supported
H9	BIA → APIP	Direct	0.369			7.354	0.000	Supported
H10	ORS → BIA → APIP	Mediation	0.333	0.223	0.556	6.735	0.000	Partial Mediation
H11	HC → BIA → APIP	Mediation	0.167	0.056	0.223	3.472	0.000	Partial Mediation
H12	TIR → BIA → APIP	Mediation	0.114	0.062	0.176	3.703	0.000	Partial Mediation
H13	EEF → BIA → APIP	Mediation	0.118	0.044	0.162	2.688	0.001	Partial Mediation

Table 10 illustrates that the structural equation modeling investigation demonstrated substantial correlations among all proposed pathways. The results indicate that organizational readiness for change (ORS) has the most significant direct influence on business intelligence adoption (BIA) ($\beta = 0.603$, $p < 0.001$), followed by a considerable effect on audit process improvement performance (APIP) ($\beta = 0.333$, $p < 0.001$). Technology Infrastructure Readiness (TIR) and Human Capital (HC) exhibited similar impacts on BIA ($\beta = 0.168$, $p < 0.001$; $\beta = 0.151$, $p < 0.001$, respectively), but External Environmental Factors (EEF) revealed a notable albeit comparatively lesser effect ($\beta = 0.119$, $p < 0.001$). BIA was identified as a significant predictor of APIP ($\beta = 0.369$, $p < 0.001$), underscoring its essential function in the model.

The mediation study, as shown in Table 10, demonstrated significant indirect effects via BIA across all proposed mediating relationships. In the ORS→BIA→APIP pathway, the most important mediation effect was found (indirect effect = 0.223), with BIA acting as a partial mediator and a total effect of 0.556. This discovery highlights the dual method by which organizational preparation affects audit process enhancement—both directly and via improved business intelligence adoption. The role of BIA as a mediator was also proven in the connections between HC and APIP (indirect effect = 0.056, total effect = 0.223), TIR and APIP (indirect effect = 0.062, total effect = 0.176), and EEF and APIP (indirect effect = 0.044, total effect = 0.162). The results always show that there are some partial mediation effects. This means that even though BIA greatly increases the effect of organizational factors on improving the audit process, direct effects are still very big and important. This trend indicates a complicated interaction among organizational capacities, technological adoption, and performance enhancement inside the auditing framework.

3.5 Additional Analyses

3.5.1 PLS Predict Analysis Results

Table 11 presents the PLS predict analysis results, including Q^2 predict values, RMSE, and MAE for both PLS-SEM and Linear Model (LM)

Table 11 PLS Predict Analysis

Indicator	Q^2_predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE	RMSE_diff
APIP1	0.535	0.597	0.462	0.620	0.484	-0.023
APIP2	0.533	0.564	0.452	0.594	0.476	-0.030
APIP3	0.601	0.555	0.436	0.582	0.457	-0.027
APIP4	0.512	0.652	0.513	0.679	0.538	-0.027
APIP5	0.571	0.569	0.448	0.591	0.472	-0.022
BIA1	0.480	0.662	0.530	0.682	0.546	-0.020
BIA2	0.520	0.551	0.434	0.583	0.461	-0.032
BIA3	0.496	0.592	0.467	0.624	0.501	-0.032
BIA4	0.464	0.628	0.503	0.636	0.508	-0.008
BIA5	0.394	0.612	0.491	0.631	0.503	-0.019

According to Table 11, the entire indicators exhibit positive Q2 predict values that range from 0.394 to 0.601, which indicates that the model has a solid capacity to predict the future. To be more specific, the APIP3 indication demonstrates the highest Q2 predict value (0.601), followed by the APIP5 indicator (0.571), which demonstrates a particularly good predictive power for the APIP construct.

3.5.2 Cross-Validated Predictive Ability Test (CVPAT)

Table 12 Cross-Validated Predictive Ability Test (CVPAT)

	CVPAT - PLS SEM vs Indicator Average (IA)					CVPAT - PLS SEM vs Linear Model (LM)			
	PLS loss	IA loss	Average loss difference	t value	p value	LM loss	Average loss difference	t value	p value
APIP	0.346	0.769	-0.423	7.573	0.000	0.378	-0.032	5.012	0.000
BIA	0.372	0.705	-0.333	7.133	0.000	0.400	-0.027	4.548	0.000
Overall	0.359	0.737	-0.378	7.886	0.000	0.389	-0.029	6.872	0.000

The PLS-SEM model significantly outperforms both benchmarks, as evidenced by the results in Tables 12. The APIP construct exhibits a loss difference of -0.423 (t-value = 7.573, $p < 0.001$) in comparison to IA (Table 2a), whereas BIA exhibits a difference of -0.333 (t-value = 7.133, $p < 0.001$). In general, the model exhibits a loss difference of -0.378 (t-value = 7.886, $p < 0.001$). The PLS-SEM model's predictive strength is further validated by the comparison with LM, which also affirms its superiority, albeit with smaller but still significant loss differences.

3.5.3 Effect Size Analysis

Table 13 f-Square (f^2)

Variables	APIP	BIA	EEF	HC	ORS	TIR
APIP						
BIA	0.191					
EEF	0.046	0.035				
HC	0.097	0.060				
ORS	0.187	0.782				
TIR	0.040	0.067				

Using Cohen's criteria, f^2 values of 0.02, 0.15, and 0.35 suggest minor, medium, and large effects, respectively. The analysis in Table 13 shows: ORS had the greatest impact on BIA (f^2 = 0.782), indicating a significant impact. BIA and

ORS have moderate effects on APIP (f^2 = 0.191 and 0.187, respectively). HC and EEF have significant but minor impacts (f^2 = 0.097 and 0.046, respectively).

3.5.4 Importance-Performance Map Analysis (IPMA)

Table 14 presents the IPMA results, combining performance scores for each construct.

Construct	Performance Score
APIP	55.019
BIA	52.194
EEF	53.440
HC	58.535
ORS	48.056
TIR	49.872

IPMA statistics show that HC has the greatest performance score (58.535). APIP is second (55.019), EEF is modest (53.440) and Lowest performance score is ORS (48.056). Table 14 shows that ORS has a big effect size but low performance, recommending management improvement.

Several conclusions may arise from the extensive supplementary analysis. The model exhibits robust predictive capabilities, as indicated by the favorable Q2 predictive values shown in Table 11. As shown in Table 12, the results of the Cross-Validated Predictive Ability Test (CVPAT) show that the model is even better at making predictions than current standards. Secondly, there is a substantial effect size of f^2 = 0.782, which indicates that organizational readiness and support (ORS) has the most significant impact on business intelligence adoption (BIA) in terms of connection strengths. Additionally, both BIA and ORS exhibit moderate effects on Agricultural Performance Improvement (APIP), whereas Human Capital (HC) and External Environmental Factors (EEF) manifest diminished, yet still significant, effects. Thirdly, the model accounts for 77.2% of the variance in APIP and 68.2% of the variance in BIA, demonstrating considerable explanatory capacity. Ultimately, we recognize ORS as a critical area for enhancement; despite its significant impact, its performance remains relatively inadequate. Enhancing ORS could yield substantial gains in overall performance.

3.6 Qualitative Analysis

The theme analysis of semi-structured interviews with twelve key stakeholders revealed significant insights that improved the quantitative findings. The analysis yielded three primary topics: Strategic Deployment Challenges: The participants consistently underscored the critical significance of executive management support for the successful deployment of business intelligence. In the absence of robust leadership support, even the most advanced BI tools become obsolete, according to one IT manager. This theme substantially corroborated the quantitative results regarding organizational readiness. Technical Integration Challenges: The respondents identified specific challenges in the integration of BI technologies with the existing infrastructure. This was said by a senior director of information technology. "Our primary challenges were issues with data quality and compatibility with legacy systems," With the help of this qualitative insight, a more in-depth comprehension of the major impact that the technology infrastructure build has on the quantitative analysis was achieved. The need of ongoing training and skill development was stressed by stakeholders in the field of human resource development. A proprietor of an agricultural company said, "We found that consistent training sessions and knowledge-sharing initiatives significantly increased the adoption of business intelligence." The quantitative findings addressing the influence of human capital capabilities on the adoption of business intelligence were supported by this subject, which provided further evidence.

4. Discussion

This study offers an in-depth analysis of the implementation of business intelligence (BI) within the agricultural sector, with a focus on North Sulawesi. Many important things, like how ready the technology infrastructure is (TIR), how much support there is for organizational readiness (ORS), how skilled the human capital is (HCC), and the impact of outside environmental factors (EEF), have a big impact on the use of BI and the success of agricultural process innovations (APIP). This presentation will elaborate on the implications of these results, their integration with existing research, and the practical insights they offer for professionals in the agribusiness sector.

This study, like earlier ones that stressed the need for strong IT systems for digital transformation (Jiménez-Partearroyo & Medina-López, 2024), shows how important TIR is for encouraging the use of BI. In our sample, TIR improved both BI adoption and APIP. This shows that a well-established technological infrastructure not only makes it easier for people to use BI tools, but it also makes farming innovation processes work better. Based on this result, agribusinesses in developing areas should put money into high-quality, scalable data tools to help them make better decisions and come up with new ideas.

ORS was the strongest predictor of BI adoption, supporting the idea that leadership commitment, resource allocation, and an innovation-friendly culture are crucial to BI implementation. ORS directly influences APIP through BI adoption, demonstrating the revolutionary power of organizational readiness. This supports Bordeleau et al. (2020) and emphasizes leadership in digital changes. Notably, ORS' modest performance score suggests improvement. Enhancing

ORS could boost BI adoption and APIP; thus, agricultural leaders must aggressively promote BI efforts. HCC—including technical and analytical skills—also boosts BI adoption and APIP.

Qualitative findings underscore the necessity of ongoing training and knowledge-sharing in developing BI-competent workers. These findings support the discussion of human resources in digital transformation that Geng et al. (2024) presented. On the other hand, HCC had a smaller impact on APIP than ORS did, which suggests that talented human resources are essential but insufficient in the absence of organizational support. That being said, the implementation of BI necessitates both technological skills and organizational support.

EEF has a minor but significant impact on BI adoption and APIP, supporting the premise that market constraints, regulations, and industry trends influence technology adoption (Pawlak & Kołodziejczak, 2020). This study emphasizes contextual factors' impact on agribusinesses' BI adoption. To encourage technology adoption by agribusinesses, especially those with limited resources, policymakers and industry associations might examine these external effects and provide incentives and frameworks.

The study found that BIA partially mediates the link between four major variables (TIR, ORS, HCC, and EEF) and APIP, with the largest influence in the ORS → BIA → APIP pathway. This suggests that organizational readiness, technology, and human capital work better together to innovate using BI systems, enabling performance increases. This supports Gabriel and Gandorfer (2023) by showing that BI adoption links organizational and environmental resources to agribusiness innovation outcomes.

5. Theoretical and Practical Implications

This study develops a sector-specific variable model for BI and agribusiness research. It contextualizes BI adoption in agribusiness to fill the knowledge gap and provide a framework for digital agricultural researchers and practitioners. Agribusiness managers must invest in technological and organizational readiness, supported by qualified human resources, to optimize BI utilization and innovation performance. The report also emphasizes the importance of an enabling policy environment, indicating that government and industry entities can facilitate BI adoption through infrastructural assistance and training.

6. Limitations and Research Directions

This study provides useful insights, but its geographical concentration on North Sulawesi may limit its generalizability. To validate the paradigm, future studies might examine BI uptake in diverse agricultural regions and circumstances. Longitudinal data may also reveal how BI adoption changes and affects performance.

7. Conclusion

This study analyzes business intelligence (BI) adoption in North Sulawesi's agribusiness industry and finds several key success variables that affect its implementation. Research shows that organizational readiness support (ORS) is the most important aspect, emphasizing leadership commitment, resource allocation, and innovation. This confirms the findings of previous research, which suggests that strategic alignment and top management support enhance the adoption of business intelligence. Another key predictor, Technology Infrastructure Readiness (TIR), confirmed the need for a strong IT infrastructure for data integration and BI tool use. To improve agriculture decision-making, invest in scalable, high-quality technological systems.

Human Capital Capability (HCC) also matters, demonstrating that skills are essential for employing BI systems. Organizational support moderates its impact, demonstrating that even the most skilled personnel needs a supportive environment to realize BI adoption benefits. Though less influential, External Environmental Factors (EEF) nevertheless influence technological adoption, highlighting market dynamics, regulatory pressures, and industry trends. This model explains 77.2% of APIP and 68.2% of BI adoption, showing significant explanatory power. These findings demonstrate to agriculture managers and policymakers the need to balance technology, organizational support, and human capital development to enhance innovation and operational efficiency.

To optimize BI adoption benefits, the study recommends improving ORS and IT infrastructure. Continuous training and knowledge-sharing can also assist in establishing a BI-savvy team. The framework provides a roadmap for developing area agribusiness players to increase competitiveness and sustainability in a fast-changing digital context. To confirm and extend these findings, future studies should examine the long-term effects of BI adoption on agriculture performance across regions.

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Conflict of Interest

The author declares that there is no conflict of interest in preparing this report, research, or document that could influence the results or interpretation of the data and analysis presented. Every step in this research has been carried out in accordance with the principles of academic and professional ethics and upholds objectivity and transparency.

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