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RESEARCH ARTICLE
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Smart Empowerment of Corn Agribusiness Actors in West Java, Indonesia: A Structural Equation Modeling Approach

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ABSTRACT

Numerous empowerment efforts for corn agribusiness actors have been implemented in developing countries; however, their effectiveness remains constrained by conventional approaches with limited outreach and failure to integrate digital technology. This study investigates factors influencing the smart empowerment of corn agribusiness actors and develops an integrated empowerment model. Conducted in West Java, Indonesia, this mixed-methods research combined survey data from 710 actors across all agribusiness subsystems with focus group discussions. Data were analyzed using Structural Equation Modelling with LISREL 8.80. The developed model demonstrates excellent fit with empirical data (RMSEA=0.064; CFI=0.98; GFI=0.90). Personal characteristics emerged as the strongest predictor of readiness (β=0.34), followed by business characteristics (β=0.27), technology service attributes (β=0.25), and social capital (β=0.19). Readiness was confirmed as a key mediator affecting empowerment (β=0.52), alongside direct effects of social capital (β=0.32) and technology attributes (β=0.19). The model explains 82% of the variance in empowerment. The novelty lies in two contributions: (1) a framework that simultaneously integrates technological innovation with social capital strengthening; and (2) the finding that readiness functions as a full mediator a prerequisite condition in the empowerment process, confirming a staged approach often overlooked in conventional programs. Practically, empowerment programs must prioritize individual motivation, context-compatible technology, and social capital strengthening before targeting final outcomes.

Keywords: Smart empowerment, Corn, Agribusiness actors, Readiness.

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INTRODUCTION

Corn (*Zea mays* L.) is one of the most important agricultural commodities globally, with global production reaching approximately 1.23 billion metric tons in 2024, serving as a major source of food, industrial raw material, and primary feed ingredient in the global livestock production system. Corn accounts for approximately 40% of coarse grain production worldwide, with the top producers being the United States, China, Brazil, Argentina, and Ukraine. The crop's versatility spanning food, feed, fuel, and fiber has positioned it as a strategic commodity for both food security and industrial development (FAO, 2025). The continuously increasing global demand for animal protein and biofuels has intensified production pressure, particularly in developing countries where smallholder farmers constitute the backbone of agricultural systems. Global meat consumption is projected to increase by 14% by 2030, driving further demand for corn as animal feed (Erenstein et al., 2022; FAO, 2024). Current projections indicate that corn demand is expected to increase by 30% by 2050, underscoring the importance of developing sustainable empowerment models capable of enhancing productivity while ensuring equitable benefits for all actors across the agribusiness value chain. This demand growth will require an additional 200 million tons of corn annually by mid-century, placing tremendous pressure on production systems in developing countries (World Bank, 2025).

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Despite its importance, global corn production faces multiple interrelated challenges. Climate change poses a significant threat, with each 1°C increase in global temperature projected to reduce corn yields by 7-10% (Tran et al., 2025). Additionally, post-harvest losses in developing countries range from 15-30% due to inadequate storage, processing, and transportation infrastructure (World Bank, 2025). These losses disproportionately affect smallholder farmers who lack access to modern technologies and market information. Furthermore, the volatility of global grain prices exacerbated by geopolitical tensions, supply chain disruptions, and energy price fluctuations creates uncertainty for farmers' investment decisions and limits their capacity to adopt productivity enhancing innovations.

In the Southeast Asian region, corn production has grown steadily by approximately 1.5–2% annually to meet the continuously increasing demand from the rapidly expanding livestock and bioenergy sectors. The region's poultry industry has grown at an average rate of 5-7% annually over the past decade, driven by rising middle-class incomes and urbanization. This growth has positioned Southeast Asia as a net importer of corn, with imports reaching approximately 15 million tons annually. However, similar to the situation in many developing countries, this region continues to face challenges related to low productivity, fragmented value chains, and limited technology adoption among small-scale producers (Erenstein et al., 2022; FAO, 2024). Finger (2023) and Yang et al. (2024) revealed that the convergence of these regional challenges, alongside global market dynamics, creates both opportunities and imperatives for innovative agricultural empowerment approaches that leverage digital technology and collaborative networks.

The concept of smart agriculture has gained international attention as a transformative approach to addressing productivity and sustainability challenges in crop production systems. Choruma et al. (2024) demonstrated the potential of digital technologies to improve smallholder farmers' access to markets, information, and financial services. However, the integration of these technological solutions into comprehensive empowerment frameworks encompassing social, economic, and institutional dimensions remains limited, particularly within the context of corn agribusiness in developing countries (Smidt & Jokonya, 2022; Ma et al., 2023).

Indonesia is the largest corn producer in Southeast Asia, with production reaching 15.14 million tons in 2024 (Central Bureau of Statistics, 2025a). Corn has been designated as a strategic food commodity due to its diverse functions in the food, feed, fuel, and fiber industries. This makes corn a primary focus of agricultural development initiatives across the archipelago. West Java Province represents a clear example of the paradox within Indonesia's corn sector, where the highest national productivity achievement (74.75 quintals/hectare) has not been directly proportional to improvements in the welfare of agribusiness actors (Central Bureau of Statistics, 2025b). Ciamis Regency, as one of the main production centers, has in fact shown a declining production trend despite having supportive agroecological conditions and continuously growing local demand from the poultry industry. These limitations are further exacerbated by an aging farmer population, limited educational attainment, and small-scale operational capacities, all of which hinder innovation adoption and business growth (Cahyani et al., 2025; Hakim et al., 2025).

Conventional empowerment approaches have proven inadequate in addressing these complex challenges. Existing interventions generally follow a top-down implementation model characterized by sectoral fragmentation and project-based orientation (Liao et al., 2024). These approaches primarily focus on cultivation improvement and land expansion while neglecting comprehensive value chain development and technological innovation. The limitations of conventional methods are particularly evident in their narrow scope and temporary impact. Previous interventions have achieved some success in increasing productivity, yet they have failed to establish sustainable empowerment systems that integrate all agribusiness subsystems (Li et al., 2024; Prajapati et al., 2025). The absence of collaborative mechanisms and technological integration has constrained the potential for transformative change across the entire corn value chain. The era of digital transformation presents unprecedented opportunities to rethink agricultural empowerment strategies. High internet penetration rates and the emerging concept of Society 5.0 create favorable conditions for technology-based approaches capable of overcoming traditional limitations (Zengin et al., 2021; Dhanaraju et al., 2022). These technological advancements are aligned with the growing recognition of the need for more holistic and participatory empowerment models in agricultural development.

This study introduces smart empowerment as an integrative framework that simultaneously combines technological innovation with social capital development, an approach that has not been comprehensively undertaken in previous studies. This concept offers a gradual collaborative approach that not only utilizes digital tools but also strengthens social networks and individual capacities. Specifically, this research examines how social capital, personal characteristics, business characteristics, and the attributes of smart technology services influence smart readiness, as well as how smart readiness, together with social capital and technology, drives smart empowerment. The ultimate objective is to develop a comprehensive smart empowerment model capable of enhancing competitiveness, sustainability, and welfare for all actors across the corn agribusiness value chain, rather than being limited to only one subsystem.

MATERIALS & METHODS

Research Design

This study employed a positivist paradigm with a mixed-methods design, utilizing a survey approach to evaluate the smart empowerment of corn agribusiness actors in West Java, Indonesia. Data analysis was conducted using Structural Equation Modelling (SEM), adapted to the agribusiness context to assess the levels of smart readiness and empowerment. This methodology was grounded in the well-established SEM approaches proposed by Kline (2023) and Hair et al. (2024) and further enriched by its application in digital agricultural innovation studies (Klerkx & Rose, 2020).

Research Location

This study focuses on corn agribusiness actors by taking Ciamis Regency, West Java Province (Fig. 1), as the case study area. This location holds a strategic position as one of the major corn production centers in West Java, supported by favorable agroecological conditions characterized by the availability of suitable land, relatively stable rainfall, and soil types with strong potential for corn cultivation. Corn commodities in this region also play an important role in the food and feed supply chain, making their existence not only economically valuable but also essential in supporting the livestock subsector. Nevertheless, corn agribusiness actors in Ciamis continue to face various constraints, including limited access to modern technology, business capital, market information, and lengthy distribution chains that create dependence on middlemen. These conditions make Ciamis highly relevant as a socio-economic laboratory for developing a smart empowerment model based on digital innovation and pentahelix collaboration, particularly because the region possesses relatively strong farmer institutions through farmer groups, farmer group associations, and cooperatives, as well as a culture of mutual cooperation that can strengthen the implementation of a sustainable collaborative model (Central Bureau of Statistics, 2025b).

Sampling Strategy

The unit of analysis in this study was individual corn agribusiness actors, while the unit of observation comprised corn agribusiness actors in Ciamis Regency, including those operating within the upstream, on-farm, downstream, and supporting system subsystems. Statistically, the exact number of corn agribusiness actors in Ciamis Regency has not been recorded in detail by relevant institutions, including village governments, agricultural extension service centers, related technical agencies (the Department of Agriculture and Food Security, and the Department of Cooperatives, SMEs, and Trade), as well as the Central Bureau of Statistics. Therefore, the determination of the population and sample of corn agribusiness actors in this study was carried out through focused discussions with village governments, technical implementation units, and agricultural extension officers at the sample locations. The criteria used in sample determination were individuals actively engaged in corn agribusiness activities at the time of the study, including corn farmers, providers of farm inputs or agro-industrial inputs, corn product processors (agro-industry actors and corn-based MSME actors), service managers or providers (agricultural information providers, extension agents, plant pest and disease officers, facilitators, farmer organization managers, cooperative or farmer group association managers), distributors or marketers of corn products (collectors and suppliers), and agro corn-based creative economy actors. Actors in the on-farm subsystem were selected using the sampling technique developed by Slovin with a 95% confidence level because this subsystem had the largest population (1,686 individuals) and a high degree of heterogeneity, while also considering efficiency in terms of time, labor, and cost. Meanwhile, actors in the upstream, downstream, and supporting system subsystems, whose populations were smaller and clearly defined, were selected using the census method (total sampling) in order to obtain accurate and comprehensive information regarding the entire population without selecting only a portion of its members.

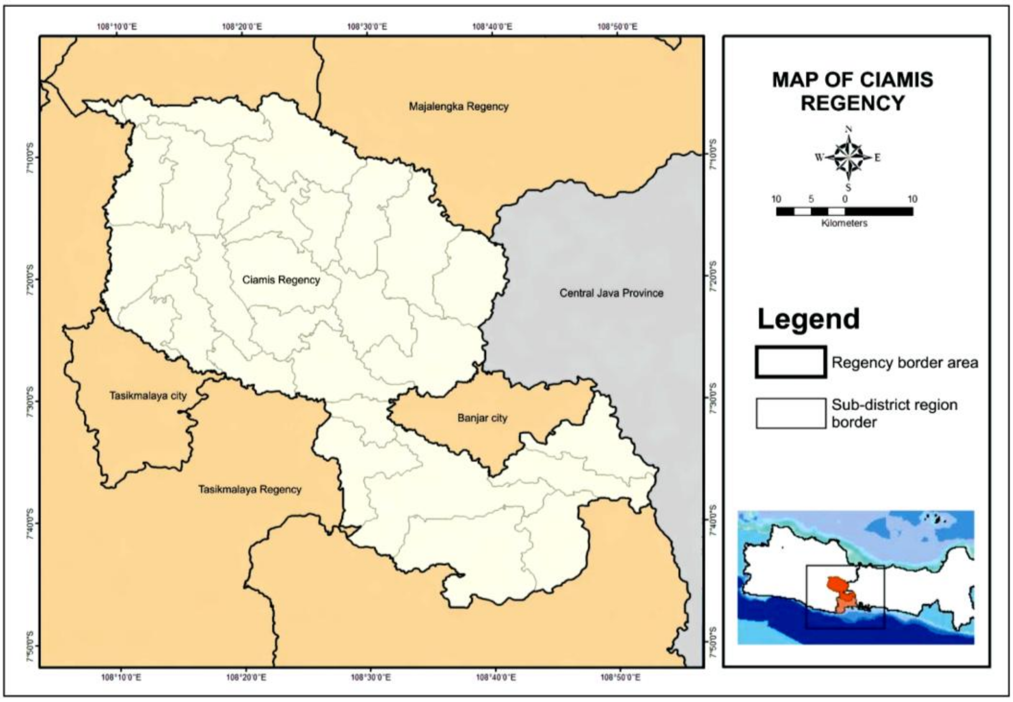

Fig. 1: Map of the Research Location.

Table 1 shows that the sample size in this study consisted of 710 respondents, indicating that it exceeded the minimum requirement for Structural Equation Modeling (SEM) analysis. According to Hair et al. (2024), SEM requires at least 5–10 observations for each estimated parameter. Since the model in this study estimated 30 parameters, the minimum required sample ranged from 150 to 300 observations. Therefore, the sample size of n = 710 was considered adequate and even exceeded the recommended minimum standard.

Table 1: Research Sample

Actors	Population (people)	Sampling Method	Sample Size (people)
Upstream agribusiness	81	Census	81
Onfarm agribusiness	1.686	Slovin Formula	323
Downstream agribusiness	104	Census	104
Supporting system agribusiness	202	Census	202
Amount	2.073		710

Variables and Indicators

This study analyzed the smart empowerment of corn agribusiness actors through six main variables: social capital, personal characteristics, business characteristics, the attributes of smart technology services, smart readiness, and smart empowerment. Each variable was evaluated using a series of indicators derived from the existing literature and modified to fit the context of corn agribusiness, as outlined in Table 2 (Friedmann, 1992; Parasuraman, 2000; Grootaert & Bastelar, 2002; Tambunan, 2002; Rogers, 2003; Mardikanto, 2009).

Data Collection

Primary data were collected using a structured questionnaire designed based on the research variables and indicators, which was subsequently tested for validity and reliability. The questionnaire employed a five-point Likert scale to measure perceptions regarding the level of social capital, personal and business characteristics, the attributes of smart technology services, the level of smart readiness, and the level of smart empowerment. Secondary data were obtained from government statistics, institutional reports, and relevant academic publications. Field research was conducted in Ciamis Regency between March and June 2024, with data collection facilitated by trained enumerators to ensure the accuracy, consistency, and completeness of responses.

Analysis Techniques

This study employed Structural Equation Modeling (SEM) using LISREL 8.80 software to test the causal relationships among latent variables. The stages of analysis were carried out as follows (Kline, 2023; Hair et al., 2024):

1. Data Preparation: Questionnaire data measured on an ordinal scale were transformed into interval scale data using the Method of Successive Interval (MSI) to meet the requirements of SEM analysis.
2. Measurement Model (Confirmatory Factor Analysis/CFA): Validity was tested through the Standardized Loading Factor (SLF) ≥ 0.40 and t-value ≥ 1.96. Construct reliability was examined using Construct Reliability (CR ≥ 0.60).
3. Structural Model: Causal relationship analysis was conducted between exogenous variables (social capital, personal characteristics, business characteristics, and the attributes of smart technology services) and endogenous variables (smart readiness and smart empowerment).
4. Model Fit Evaluation: Model adequacy was assessed using several goodness-of-fit indices, such as Chi-Square, RMSEA (≤ 0.08), and NFI, NNFI, CFI, IFI, RFI, and GFI (≥ 0.90).
5. Hypothesis Testing: The significance of structural path coefficients was tested based on t-values (≥ 1.96).

Table 2: Variable and Indicators

Variable	Operational Definition	Indicators
Social Capital (X_1)	A series of shared informal and non-formal values / norms possessed among interconnected corn agribusiness actors.	$X_{1.1}$ Trust $X_{1.2}$ Norms $X_{1.3}$ Partisipation $X_{1.4}$ Network $X_{1.5}$ Reciprocity
Personal Characteristics (X_2)	Factors inherent in corn agribusiness actors that influence their behavior and capacity in agribusiness activities.	$X_{2.1}$ Age $X_{2.2}$ Education $X_{2.3}$ Business Experience $X_{2.4}$ Motivation $X_{2.5}$ Cosmopolitanism
Business Characteristics (X_3)	Attributes inherent in the corn agribusiness business activities being undertaken.	$X_{3.1}$ Business Scale $X_{3.2}$ Type of Business Service $X_{3.3}$ Business Status $X_{3.4}$ Capital Source $X_{3.5}$ Collaboration $X_{3.6}$ Technology Ownership
Nature of Smart Technology Services (X_4)	Perceived characteristics of digital technology within the context of corn agribusiness.	$X_{4.1}$ Relative Advantage $X_{4.2}$ Compatibility $X_{4.3}$ Complexity $X_{4.4}$ Triability $X_{4.5}$ Observability
Level of Smart Readiness (Y_1)	The level of actors' readiness in socio-cultural, economic, technological, behavioral, ecosystem, and technological aspects to adopt technology-based empowerment.	$Y_{1.1}$ Socio-Cultural Readiness $Y_{1.2}$ Economic Readiness $Y_{1.3}$ Behavioral Readiness $Y_{1.4}$ Ecosystem Readiness $Y_{1.5}$ Technological Readiness
Level of Smart Empowerment (Y_2)	The level of actors' ability to access, control, and utilize resources and smart technologies in order to improve their welfare.	$Y_{2.1}$ Power to Smart $Y_{2.2}$ Power within Smart $Y_{2.3}$ Power over Smart $Y_{2.4}$ Power with Smart

Through the SEM approach, this study was able to validate the measurement constructs while simultaneously testing the causal relationships among variables, thereby providing an empirical basis for the proposed conceptual model.

RESULTS

Respondent Characteristics

The characteristics of corn agribusiness actors constitute a fundamental aspect influencing performance, efficiency, and the ability to adapt to market dynamics and technological innovation throughout the value chain. Table 3 presents the personal and business characteristics of corn agribusiness actors in Ciamis Regency according to subsystem.

Corn agribusiness actors in Ciamis Regency have an average age of 46.67 years, reflecting a late adulthood or pre-elderly stage, which indicates the need for regeneration strategies to increase the participation of younger generations in this sector. On the other hand, the educational level of actors in the on-farm and downstream subsystems is relatively lower than that of actors in the other subsystems, implying the importance of capacity building through training and mentoring to encourage innovation adoption. Nevertheless, the relatively high level of business experience (14.23 years), particularly in the downstream subsystem, demonstrates the potential of practice-based learning that can be utilized to accelerate business modernization. The business structure, which is dominated by micro-scale enterprises across almost all subsystems, indicates limitations in efficiency and competitiveness, thereby requiring strengthened access to markets and financing so that businesses can grow and move to a higher level. In addition, the predominantly individual business status reflects weak collective institutionalization, implying the need to strengthen organizations such as farmer groups or cooperatives in order to improve bargaining positions. Dependence on personal capital sources also indicates limited access to formal financing, thus necessitating broader financial inclusion. However, the relatively widespread ownership of technology in the form of smartphones provides an opportunity to accelerate agribusiness digitalization, which needs to be optimized through improved digital literacy and productive technology utilization to support a more efficient and sustainable agribusiness transformation.

Validity and Reliability of the Measurement Model

Before testing the structural model, Confirmatory Factor Analysis (CFA) was conducted to ensure that all indicators validly and reliably measured their respective latent constructs. Table 4 summarizes the results of the validity and reliability analysis of the measurement model.

Table 3: Personal and Business Characteristics of Corn Agribusiness

	Upstream	On Farm	Downstream	Supporting	Agribusiness Actors (Average)
Age (years)	46,78	47,57	47,69	44,68	46,67
Education (years)	11,06	7,69	7,64	8,34	8,25
Business Experience (years)	13,02	13,76	16,67	14,22	14,23
Business Scale	Micro	Household, Micro	Micro	Micro, Small, Large	Micro
Business Status	Individual	Individual	Individual, Group	Group, Corporation, Government	Individual
Source of Capital	Personal	Personal	Personal, Assistance	Assistance	Personal
Technology Ownership	Smartphone	Smartphone	Smartphone	Smartphone, Laptop	Smartphone

Table 4: Reliability and Validity Analysis of the Study Model

Variable	Indicator	Validity		Description	Reliability		Description
		t-value	SLF		CR Value	VE Value	
Social Capital (X_1)	X1.1	13.40	0.54	Valid	0.744	0.374	Reliable
	X1.2	17.56	0.69	Valid			
	X1.3	10.69	0.45	Valid			
	X1.4	16.42	0.65	Valid			
	X1.5	17.68	0.69	Valid			
Personal Characteristics (X_2)	X2.1	8.12	0.36	Marginal*	0.624	0.272	Reliable
	X2.2	7.33	0.32	Marginal*			
	X2.3	8.97	0.40	Valid			
	X2.4	14.69	0.78	Valid			
	X2.5	12.56	0.60	Valid			
Business Characteristics (X_3)	X3.1	13.70	0.56	Valid	0.773	0.369	Reliable
	X3.2	20.02	0.75	Valid			
	X3.3	11.32	0.46	Valid			
	X3.4	12.46	0.50	Valid			
	X3.5	15.78	0.61	Valid			
	X3.6	18.84	0.71	Valid			
Nature of Smart Technology Services (X_4)	X4.1	16.91	0.64	Valid	0.791	0.431	Reliable
	X4.2	18.27	0.68	Valid			
	X4.3	16.91	0.64	Valid			
	X4.4	17.62	0.66	Valid			
	X4.5	17.71	0.66	Valid			
Level of Smart Readiness (Y_1)	Y1.1	14.12	0.58	Valid	0.716	0.337	Reliable
	Y1.2	11.96	0.50	Valid			
	Y1.3	15.77	0.65	Valid			
	Y1.4	14.99	0.62	Valid			
	Y1.5	13.01	0.54	Valid			
Level of Smart Empowerment (Y_2)	Y2.1	11.81	0.60	Valid	0.690	0.357	Reliable
	Y2.2	12.50	0.59	Valid			
	Y2.3	12.43	0.63	Valid			
	Y2.4	12.18	0.57	Valid			

Note: Marginal = SLF < 0.40 but still statistically significant (t-value > 1.96).

Based on the Confirmatory Factor Analysis (CFA), all constructs in the research model demonstrated adequate validity and reliability. The standardized loading factor values for all indicators were within the acceptable tolerance threshold of 0.40, although two indicators (age with SLF = 0.36 and education with SLF = 0.32) were slightly below 0.40 but remained statistically significant (t-value > 1.96). Substantively, the relatively low contribution of these two indicators confirms that demographic factors are not the primary determinants in shaping smart readiness; rather, more internal and contextual factors play a stronger role. This is reflected in the dominance of motivation (SLF = 0.78) within the personal characteristics construct, indicating that internal drive has a greater influence than demographic attributes. Within the business characteristics construct, the type of business services (SLF = 0.75) emerged as the key indicator, suggesting that the level of service diversification affects readiness to adopt technology. Meanwhile, in the construct of the attributes of smart technology services, compatibility (SLF = 0.68) became the dominant indicator, emphasizing that technologies aligned with local needs, values, and conditions tend to be more easily adopted. For the endogenous variables, behavioral readiness (SLF = 0.65) within smart readiness indicates that psychological aspects such as attitudes and beliefs are more decisive than infrastructural readiness, whereas control capacity (SLF = 0.63) within smart empowerment confirms the importance of actors' ability to access and manage resources as the central dimension of empowerment. In addition, the construct reliability (CR) values for each variable exceeded the critical threshold of 0.60, ranging from 0.624 to 0.791, which indicates good internal consistency. The highest CR value was found in the variable of the attributes of smart technology services (0.791), showing that its indicators consistently reflected the construct being measured. Overall, these findings confirm that the measurement model possesses strong psychometric quality and is appropriate for use in further analysis.

Evaluation of Structural Model Fit

The evaluation of structural model fit confirms that the proposed model is consistent with the empirical data, with all goodness-of-fit indicators meeting the recommended fit criteria (Table 5). The RMSEA value of 0.064 (< 0.08) indicates an acceptable approximation error, while the GFI value (0.90) satisfies the minimum threshold for absolute fit. The incremental and comparative fit indices (NFI = 0.97, NNFI = 0.98, CFI = 0.98, IFI = 0.98), as well as the RFI value (0.96), consistently exceed the 0.90 cut-off point, indicating that the hypothesized model performs significantly better than the baseline model (independence model).

Substantively, the CFI value (0.98) and NNFI value (0.98), both approaching 1.00, indicate that the developed theoretical model is nearly perfect in reproducing the covariance matrix of the empirical data. In other words, the hypothesized causal relationships among social capital, personal characteristics, business characteristics, the attributes of smart technology services, smart readiness, and smart empowerment are empirically confirmed within the context of corn agribusiness in West Java.

Table 5: *Goodness of Fit* (GoF)

Goodness-of-Fit Measure	Value	Level of Fit
Root Mean Square Error of Approximation (RMSEA)	0.064	Good Fit
Normed Fit Index (NFI)	0.97	Good Fit
Non-Normed Fit Index (NNFI)	0.98	Good Fit
Comparative Fit Index (CFI)	0.98	Good Fit
Incremental Fit Index (IFI)	0.98	Good Fit
Relative Fit Index (RFI)	0.96	Good Fit
Goodness of Fit Index (GFI)	0.90	Good Fit

Source: LISREL 8.80 Output, Data Analysis (2025).

Direct Effects among Variables

The results of the structural model estimation using LISREL 8.80 are presented in Fig. 2 and 3. Fig. 2 displays the t-values for each causal path, while Fig. 3 presents the standardized path coefficients (standardized solution). These two Fig.s serve as the basis for interpreting the causal relationships among variables in the model.

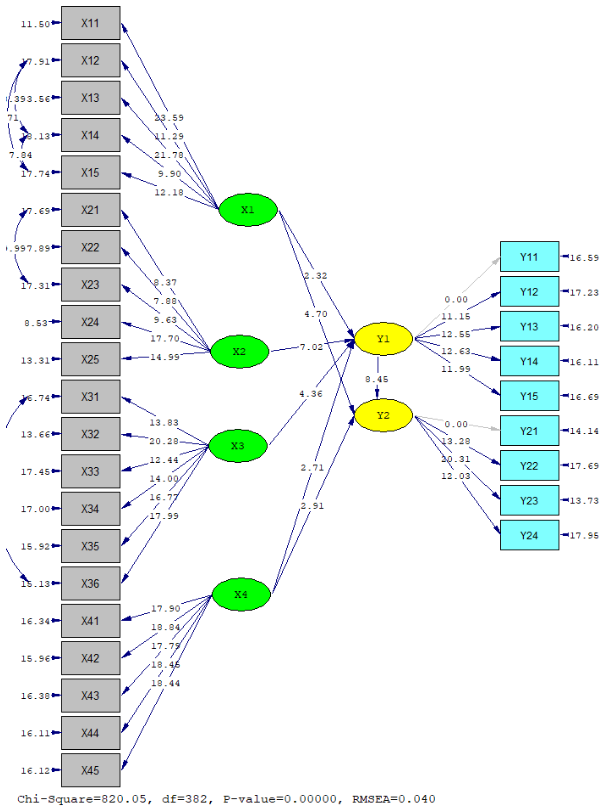

Fig. 2: Structural model with t-values for all causal paths; Source: LISREL 8.80 Output, Processed by the Researcher (2025).

To facilitate readability and avoid repetitive presentation of numerical values in the text, Table 6 summarizes all standardized path coefficients (β), t-values, and significance levels for both the direct and indirect effects in the model.

The structural model demonstrates strong predictive power for both endogenous constructs. The exogenous variables collectively explain 62% of the variance in smart readiness (R^2 = 0.62). Personal characteristics (β = 0.34; t = 6.92) emerged as the strongest predictor, followed by business characteristics (β = 0.27; t = 4.21), the attributes of smart technology services (β = 0.25; t = 2.68), and social capital (β = 0.19; t = 2.39). These findings indicate that individual internal factors, particularly motivation, are more decisive in shaping readiness for digital transformation than external factors such as infrastructural support or social networks.

Table 6: Direct Effects and R^2 Values

Path of Influence	β	t-value	Signifikansi	R^2
Direct effects on Smart Readiness (Y_1)				0,62
Social Capital (X_1) → Y_1	0,19	2,39*	t ≥ 1,96	
Personal Characteristics (X_2) → Y_1	0,34	6,92**	t ≥ 1,96	
Business Characteristics (X_3) → Y_1	0,27	4,21**	t ≥ 1,96	
Nature of Smart Technology Services (X_4) → Y_1	0,25	2,68**	t ≥ 1,96	
Direct effects on Smart Empowerment (Y_2)				0,82
Social Capital (X_1) → Y_2	0,32	4,76**	t ≥ 1,96	
Nature of Smart Technology Services (X_4) → Y_2	0,19	2,87**	t ≥ 1,96	
Smart Readiness (Y_1) → Y_2	0,52	8,46**	t ≥ 1,96	

* Significant; ** Highly significant.

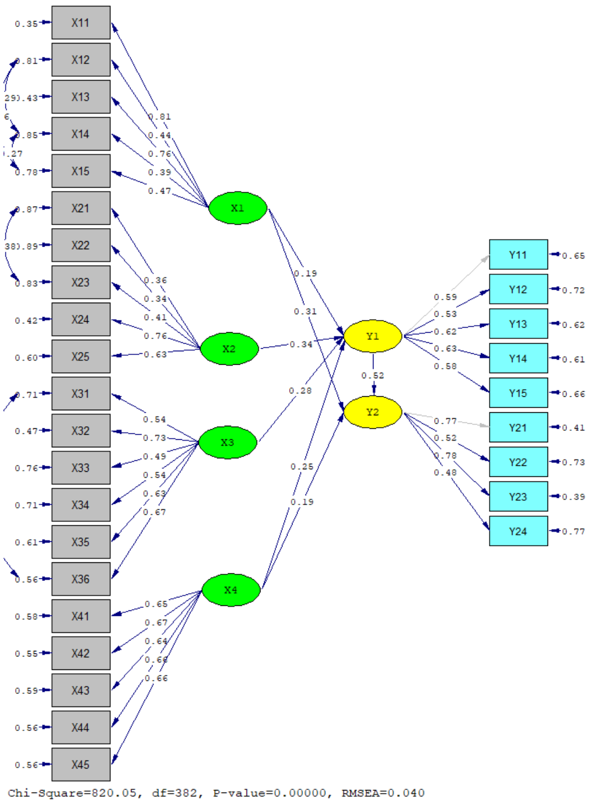

Fig. 3: Structural model with standardized path coefficients (β); Source: LISREL 8.80 Output, Processed by the Researcher (2025).

For the smart empowerment construct, the model explains 82% of the variance (R^2 = 0.82). Smart readiness exerts the strongest direct effect (β = 0.52; t = 8.46), followed by social capital (β = 0.32; t = 4.76) and the attributes of smart technology services (β = 0.19; t = 2.87). The dominance of smart readiness confirms that readiness functions as a prerequisite condition for empowerment. Without adequate readiness—technological, economic, and socio-cultural alike—any form of external intervention will not produce sustainable empowerment.

The R^2 value of 0.82 is considered exceptionally high in social science research, indicating that the developed model is nearly optimal in explaining the agricultural empowerment mechanism, which generally attains an R^2 ranging from 0.60 to 0.70 (Aziz et al., 2021; Tama et al., 2023).

Indirect Effects (Mediation)

The mediation analysis reveals that smart readiness significantly mediates the relationship between the four exogenous variables and smart empowerment (Table 7). Personal characteristics show the strongest indirect effect (β = 0.18; t = 6.09), followed by business characteristics (β = 0.14; t = 3.97), the nature of smart technology services (β = 0.13; t = 2.58), and social capital (β = 0.10; t = 2.34).

This mediation pattern carries important substantive meaning. All indirect effects are statistically significant. These findings confirm that smart readiness functions as a full mediator for personal characteristics and business characteristics. This means that personal and business characteristics will only have an impact on enhancing smart empowerment if agribusiness actors first possess adequate smart readiness.

In contrast, social capital and the attributes of smart technology services demonstrate both significant direct and indirect effects on smart empowerment, indicating that these two variables function as partial mediators. In other words, beyond improving smart readiness, social capital and technology compatibility also directly promote smart empowerment, for instance through direct access to resources or market networks. These mediation findings answer the question of why many conventional empowerment programs fail to achieve sustainable outcomes: such programs tend to skip the readiness-building stage and directly target final outcomes. A gradual approach that prioritizes smart readiness as the foundation is therefore a strategic necessity rather than merely an option.

DISCUSSION

The finding that personal characteristics constitute the strongest predictor of smart readiness (β = 0.34) confirms that individual internal factors are more decisive than external factors in the process of digital technology adoption within agribusiness. This finding is consistent with recent studies by Hoang & Tran (2023) and Šermukšnytė-Alešiūnienė & Melnikienė (2024), which found that smallholder farmers' motivation serves as the primary driver of agricultural digitalization, surpassing government infrastructural support. Tey & Brindal (2022) further added that perceived benefits and internal motivation consistently emerge as the strongest predictors across various geographical contexts.

Table 7: Indirect Effects on Smart Empowerment (Y_2)

Path of Influence (Mediation)	β	t-value	Significant
Social Capital (X_1) → Smart Readiness (Y_1) → Smart Empowerment (Y_2)	0,10	2,34*	t ≥ 1,96
Personal Characteristics (X_2) → Smart Readiness (Y_1) → Smart Empowerment (Y_2)	0,18	6,09**	t ≥ 1,96
Business Characteristics (X_3) → Smart Readiness (Y_1) → Smart Empowerment (Y_2)	0,14	3,97**	t ≥ 1,96
Nature of Smart Technology Services (X_4) → Smart Readiness (Y_1) → Smart Empowerment (Y_2)	0,13	2,58**	t ≥ 1,96

* Significant; ** Highly significant.

However, our findings extend the existing literature by identifying that motivation is far more dominant than demographic factors such as age and education. This differs from the findings of (Valdes et al., 2023) in Chile, which reported that formal education had a significant influence on farmers' production behavior. This difference is likely attributable to the characteristics of the Indonesian context, where experience-based learning plays a more substantial role than limited formal education.

An important implication of this finding is that empowerment programs in developing countries should not focus solely on improving formal education, but rather on strengthening intrinsic motivation through participatory approaches, practice-based training, and demonstrations of the tangible benefits of digital technology. This approach is highly relevant for developing countries such as Myanmar, Laos, Cambodia, as well as countries in Sub-Saharan Africa that face similar farmer profiles: mature productive age, extensive experience, but limited formal education (Choruma et al., 2024; Thi Hoa Sen et al., 2024). The finding that smart readiness functions as a full mediator for personal characteristics and business characteristics constitutes a major theoretical contribution of this study. This mediation pattern has rarely been disclosed in previous agricultural empowerment studies.

Kumari & Tiwari (2025) found that family cohesion functions as a partial mediator in agricultural performance in India. Meanwhile, Valdes et al. (2023) reported that trust mediates the relationship between internet use and farmers' production behavior in Chile. However, no full mediation pattern similar to the one reported in this study was identified. This difference indicates that within the context of corn agribusiness empowerment in Indonesia, readiness is not merely a complementary factor, but rather an absolute prerequisite condition. Without adequate readiness, any intervention, whether in the form of training, capital assistance, or technology provision, will not generate sustainable empowerment. This finding supports the readiness theory framework developed by Sharma et al. (2024) in the context of organizational digital transformation, which we now demonstrate to be equally relevant at the individual level of agribusiness actors.

Practically, these findings explain why many conventional empowerment programs fail. Such programs tend to bypass the readiness-building stage and directly target final outcomes, such as increased income, productivity, or technology adoption. The appropriate approach is therefore a gradual one: building readiness first (technological, economic, and socio-cultural), and only afterward targeting empowerment outcomes.

Social capital and the nature of smart technology services exhibit both direct and indirect effects on smart empowerment (partial mediation). This pattern indicates that these two variables perform a dual role: (1) enhancing smart readiness, and (2) directly promoting empowerment. Bešić et al. (2024) stated that in the era of Society 5.0, trust and social networks remain essential foundations for agricultural innovation. However, our study extends this finding by revealing that the direct effect of social capital on empowerment (β = 0.32) is stronger than its effect on readiness (β = 0.19). This indicates that social capital not only helps agribusiness actors become more prepared, but also directly opens access to resources, market information, and collaborative opportunities.

Meanwhile, technology compatibility as the dominant indicator (SLF = 0.68) confirms that technologies aligned with users' values, prior experiences, and practical needs are more rapidly adopted. This finding is consistent with Hoang & Tran (2023) and Singh & Kapoor (2024) who found that farmers tend to prefer agricultural platforms compatible with local practices rather than sophisticated but unfamiliar features. The implication for technology developers in developing countries is clear: the focus should not be on technological sophistication, but on contextual compatibility. Overly complex technologies may instead become barriers to adoption, particularly for actors with limited formal education.

The R^2 value of 0.82 for the smart empowerment construct further confirms that the variables in the model make a strong contribution to explaining variations in the empowerment of agribusiness actors. Conceptually, this result is in line with various SEM- and PLS-SEM-based studies in developing countries showing that empowerment is a key factor in improving agricultural performance and household welfare. Tesafa et al. (2025) in Ethiopia demonstrated that women's empowerment in agriculture enhances food security and consumption diversification through better control over resources and stronger market orientation. Likewise, Nadeem et al. (2023) and Haque et al. (2024) in Pakistan and Bangladesh found that empowerment dimensions such as decision-making, asset control, legal rights, and access to technology contribute to greater adoption of sustainable agricultural practices as well as reduced food vulnerability.

In addition, social and institutional aspects have proven to play an important role in strengthening empowerment. Phali et al. (2025) showed that participation in socio-political structures and resource governance enhances farmer engagement as well as the effectiveness of farm management. Suárez et al. (2022) and Mgema et al. (2025) also emphasized that social capital, particularly linkages with institutions and participation in organizations, exerts a significant influence on welfare improvement beyond purely physical factors. In the agribusiness context, Kolapo et al. (2022) and Bazán Valque et al. (2025) demonstrated that empowerment through social networks, resource access, and entrepreneurship is capable of increasing income and reducing poverty. Therefore, the high R^2 value in this study indicates that smart empowerment, which encompasses behavioral aspects, access to resources, and institutional support, is a highly determining factor in promoting agribusiness performance and sustainability in developing countries.

The findings of this study offer transferable insights for other developing countries facing similar agribusiness structures, particularly in Southeast Asia, Sub-Saharan Africa, and Latin America. First, the gradual approach that prioritizes the development of smart readiness before targeting empowerment outcomes is highly relevant for countries that are still in the early stages of agricultural digital transformation. A direct leap toward Agriculture 4.0 technologies without an adequate readiness foundation is likely to fail. Second, strengthening the intrinsic motivation of agribusiness actors must become the central focus of empowerment programs, rather than merely providing technological infrastructure. Demonstration plots, practice-based training, and long-term mentoring are more effective than one-time training sessions or equipment assistance. Third, digital technologies developed for smallholder farmers must prioritize compatibility with local conditions. Simple interface language, affordable access costs, and the ability to operate offline in areas with limited internet connectivity become key determinants of successful adoption. Fourth, strengthening social capital through farmer groups, cooperatives, and partnerships with agricultural extension agents remains relevant even as digitalization advances. Social networks not only facilitate technology adoption but also directly open access to markets and resources.

Limitations

Although this study provides valuable insights into the smart empowerment model for corn agribusiness, several limitations need to be acknowledged. This research was conducted within a specific geographical context (Ciamis Regency, West Java) with an exclusive focus on corn commodities, which may limit the generalizability of the findings to other regions or agricultural commodities. The cross-sectional nature of the data restricts our ability to establish causal relationships definitively or to observe empowerment dynamics over time. In addition, this study relies heavily on self-reported data, which may be influenced by social desirability bias, particularly regarding technology adoption and perceptions of empowerment. The sampling approach, although comprehensive, may have overlooked some marginal actors within the agribusiness ecosystem. Furthermore, this study did not explore in depth external factors such as market fluctuations, climate change impacts, or the broader policy environment that may also influence empowerment outcomes.

Conclusion

This study validates a smart empowerment model for corn agribusiness actors in Indonesia that explains 82% of the variance in smart empowerment (R^2 = 0.82; RMSEA = 0.064; CFI = 0.98). Smart readiness functions as a full mediator (β = 0.52), confirming that technological and psychological readiness must precede empowerment outcomes—a sequential process that is often overlooked in conventional programs. Therefore, two policy implications can be drawn. First, empowerment programs should adopt a gradual approach that prioritizes smart readiness before targeting final outcomes. Second, interventions need to simultaneously strengthen both the internal and external factors of corn agribusiness actors, as the integration of these two dimensions is the key to sustainable transformation.

Theoretical Implications

This study provides several significant contributions to the agricultural empowerment literature. First, it extends traditional empowerment theory by integrating the dimension of digital technology, thereby creating a framework that is more relevant to the Society 5.0 era. Second, this study advances our understanding of mediation mechanisms in the empowerment process, particularly the crucial role of Smart Readiness as a bridge between resources and outcomes. Third, it provides empirical validation for the capability approach in the agricultural context by demonstrating how various factors contribute to building actors' capabilities. Fourth, this research enriches the technology adoption literature by showing how the attributes of technology services interact with social and personal factors within the empowerment context. Finally, this study contributes to methodological advancement through a comprehensive SEM approach to measuring complex empowerment constructs.

Practical Implications

These findings offer several practical implications for agricultural development practitioners and extension services. First, empowerment initiatives should adopt a gradual approach by prioritizing the development of Smart Readiness before targeting empowerment outcomes. Second, interventions need to address multiple dimensions simultaneously, technological, social, and personal, rather than focusing on a single aspect. Third, technological solutions should prioritize compatibility with local contexts and existing knowledge systems to ensure successful adoption. Fourth, programs should leverage existing social capital while gradually introducing modern entrepreneurial values. Fifth, extension services need to develop differentiated approaches for different agribusiness subsystems, recognizing their distinct characteristics and needs. Finally, digital literacy programs should move beyond basic access and focus on meaningful applications within business operations.

Policy Recommendations

Based on these findings, several policy recommendations emerge. First, the government should develop integrated empowerment programs that simultaneously address technological infrastructure, human capacity development, and social capital strengthening. Second, agricultural policies need to recognize and support the diverse needs of different agribusiness subsystems through targeted interventions. Third, digital transformation policies should prioritize context-appropriate technologies that are aligned with local capabilities and needs. Fourth, educational policies should incorporate digital literacy and agribusiness management into agricultural extension curricula. Fifth, financial policies need to address the financing constraints of micro-scale agribusiness through innovative funding mechanisms. Finally, local governments should promote penta-helix collaboration involving academia, business, community, government, and media in order to create a sustainable empowerment ecosystem.

Future Research

This study opens several avenues for future research. First, longitudinal studies are needed to examine how empowerment dynamics evolve over time and across different stages of technology adoption. Second, comparative research across various commodities and geographical contexts would enhance the generalizability of the smart empowerment framework. Third, future studies may explore the role of external factors such as climate change, market integration, and the policy environment in shaping empowerment outcomes. Fourth, research focusing on specific demographic groups, particularly youth and women in agribusiness, would provide valuable insights for targeted interventions. Fifth, action research that implements and refines the proposed model in different contexts would contribute to both theoretical and practical advancement. Finally, studies examining the impact of emerging technologies such as blockchain, IoT, and AI on agricultural empowerment will help maintain the relevance of this framework in a rapidly evolving technological landscape.

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