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Analysis of technology adoption and government policy in improving the financial performance of SMEs in the Indonesia agricultural sector

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Abstract
Agriculture micro, small, and medium enterprises (MSMEs) have an important function but face problems in improving financial performance, including low net income of agricultural commodities per season, low yields per hectare, and low added value of processed agricultural products. The study aimed to analyze the effects of technology-based acceleration programs, digital literacy, and agricultural technology on financial sector performance in MSMEs within the agricultural sector in South Sumatra Province, Indonesia. The analysis method employed SEM-PLS on survey data collected from 160 respondents proportionally representing 13 regencies and four cities in South Sumatra Province. The independent variables consisted of the intensity of participation in technology-based acceleration programs, including mentoring, training, incubation, agricultural product development, and entrepreneurship. It also included digital literacy, such as mastery of smart agricultural applications, the ability to analyze harvest data and soil quality, and skills in innovating with agricultural technology, as well as government policies, including financing and access to credit, subsidies, and social assistance, training, and capacity building. The dependent variable focused on the improvement in financial performance, which included the level of income from agricultural commodities per season and net profit per season. The results of this study showed that the output of the R-Square SEM-PLS model indicated that participation in technology-based acceleration programs had a significant effect on the financial performance of MSMEs in the agricultural sector. Improving financial performance was also supported by digital literacy, which included applying intelligent agricultural skills, analyzing harvest data and soil quality, and the ability to innovate with digital technology. Technology-based acceleration programs, digital literacy, modern agricultural technology, and government policies collectively contributed to improving financial performance in MSMEs within the agricultural sector.

Keywords: Technology-based acceleration program, Digital literacy, Agricultural technology, Net sales of agricultural commodities per season, Productivity/yield per hectare

1. Introduction

Micro, small, and medium enterprises MSMEs in the agricultural sector were one of the sectors as a driver of Indonesia's economy [1]. From MSME there were around 65.5 million MSME units spread across Indonesia and absorb up to 97.2% of the total workforce. One of the main sectors of MSMEs was agriculture (food, horticultural crops, plantations, livestock cultivation, and fisheries and forestry), where its contribution to the Gross Domestic Product increased by 61.1% [2], [3]. This shows the important role of MSMEs in the national economy. Despite being the main sector, MSMEs in Indonesia still face many problems in improving financial performance. Several factors that influence this include limited access to modern agricultural technology to support productivity and added value of commodities [4], [5]. In addition, low digital literacy possessed by business actors also hinders the implementation of good agricultural practices based on data and analytics to support business efficiency [6], [7].

Similar conditions also occur in India, which was the third largest agricultural country in the world. The MSME agricultural sector in India provides employment for around 111 million people and contributes 30% to the national GDP. However, in fact, there were still problems with the low managerial capacity of small farmers to manage business risks and utilize technology [8]. In Vietnam, a major agricultural commodity exporting country, the contribution of agricultural sub-sector MSMEs reaches 25% of the total agricultural sector output and absorbs 54% of the agricultural workforce [9]. Meanwhile, in the United States, which was the country with the largest agricultural production in the world, the role of MSMEs in the agricultural subsector to total agricultural output reaches 33%, where this sector also absorbs 32% of agricultural labor. Aladawiya & Fidhyallah [10] said that digital literacy and access to agricultural technology affect the performance of MSME businesses in the agricultural sector, including output, income, and business efficiency. This was proven by his research that was conducted on Arabica coffee in Kulon Progo, Yogyakarta, in 2021. Furthermore, Abdullah et al. [11] said that farmers who use AI assistants experience an average increase in productivity and profits of 20%. AI was used to provide advice on seed types, harvest times, optimal selling prices, and early detection of pests. This study indicates the great potential of technology in strengthening the resilience of smallholder farmers through better risk management. Based on this study, various differences between this study and previous research could be used as a comparison.

First, the scope of this study was broader because it covers agricultural MSMEs in general in the Province of South Sumatra, Indonesia, while previous studies were more specific to Arabica coffee commodities in Kulon Progo. Second, this study would add analysis variables, namely digital-based acceleration and government policies, in contrast to previous studies, which only focused on digital literacy, technology access, and productivity. Third, this study takes a broader perspective on modern agricultural technology, differing from previous research that focused solely on AI assistants. The theory underlying the relationship between technology-based acceleration, digital literacy, and increased financial performance in the agricultural MSME sector was:

1) Rogers' [12] diffusion of innovation theory, which explained how the process of accelerating the spread of technology and innovation could be accepted and applied by individuals or organizations within a community.
2) 2) The dynamic capabilities theory, which explained the ability of individuals or organizations to adapt to their environment, such as the shift from manual technology to digital literacy, was seen as a capability that allowed MSMEs to utilize technological advancements to improve their performance in the agricultural sector.

From the various phenomena that have been explained, so:

1) Examined how to accelerate technology-based programs with the goal of improving the financial performance of MSMEs in the agricultural sector. This study evaluated various program aspects,

including mentoring, training, incubation, funding, program duration, and learning components such as digital literacy, agricultural product development, and entrepreneurship.

2) It examined the function of digital literacy in supporting the financial performance of MSMEs in the agricultural sector, focusing on proficiency in smart farming applications, the ability to analyze harvest data and soil quality, and skills in innovating with agricultural technologies.
3) The research also analyzed the application of agricultural technology in boosting the financial performance of MSMEs, particularly through the adoption of post-harvest technologies and e-commerce solutions.
4) Additionally, it assessed the influence of government policies on enhancing the financial performance of MSMEs in the agricultural sector, with an emphasis on access to financing and credit, subsidies and social assistance, training, and capacity building, and the promotion of agricultural digitalization.

2. Research method

The study was conducted in South Sumatra Province, Indonesia, for 2 months, from May to September 2024. The sample determination used a non-probability sampling technique. Sample selection with the criteria of farmers who are farming and have a business or marketing chain for harvested products. The population contacted was 350 people, and the number of confirmed samples was 160 people. All samples in this study were MSMEs in the agricultural sector engaged in food commodities such as rice, vegetables, and fruits. Likert scale was used in data collection with a range of 1 to 5. SEM was a combination of factor variable analysis, as well as structural modeling and path analysis, to assess the relationships between variables comprehensively [11]. The research model must be based on a theory or conceptual framework that underlies the relationship between independent variables (such as technology-based acceleration programs, digital literacy, agricultural MSME technology, and government policy) and dependent variables (financial performance of MSMEs in agriculture). The SEM method was chosen because it can explain both direct and indirect relationships between variables and provide insights into the simultaneous correlations between latent variables (exogenous and endogenous).

Additionally, it accounts for measurement errors and factor loadings. The SEM-PLS analysis involves the following stages:

The analysis of the external model at this stage examines how indicators can be related to other latent variables and emphasizes that the measurements used must be valid and reliable. This outer model was tested valid spread, value factor loading range 0.5 and 0.7 was considered valid [13], and AVE can be a mainstay if it was > 0.6. Furthermore, if the value (AVE) was > 0.5, it indicates that this value was more than half, and the construction can be explained as an indicator.

(2) The inner model stage refers to the structural model that helps estimate the causes and consequences of connections between latent variables, a variable that uses indirect measurement. Such as analyzing R2, namely the coefficient of determination using bootstrapping in SEM-PLS. The R2 value was divided into three categories: (1) R2 = 0.67 (strong), (2) R2 = 0.33 (moderate), (3) R2 = 0.19 (weak) [14]. Table 1 describes the variables and their respective indicators.

Table 1. Research variables and indicators

Variables	Variables Notation	Indicators	Indicator Notation
Technology-based acceleration program	X1	Type of program (mentoring, training, incubation, funding)	X11
		Program duration	X12

Variables	Variables Notation	Indicators	Indicator Notation
		Learning components (digital literacy, agricultural product development, entrepreneurship)	X13
Digital literacy	X2	Mastery of smart farming applications	X21
		Ability to analyze harvest data and soil quality	X22
		Skills to innovate with agricultural technology	X23
UKM agriculture technology	X3	Smart farming	X31
		Post-harvest technology	X32
		E-commerce agriculture	X33
Government policy	X4	Financing and credit access	X41
		Subsidies and social assistance	X42
		Training and capacity building	X43
		Digitalization of agriculture	X44
Financial performance of SMEs in the agricultural sector	Y1	Digitalization of agriculture	Y11
		Net income/sales of agricultural commodities per season	Y13
		Productivity/yield per hectare	Y14

The variables and indicators in Table 1 can be seen in the conceptual framework of Figure 1.

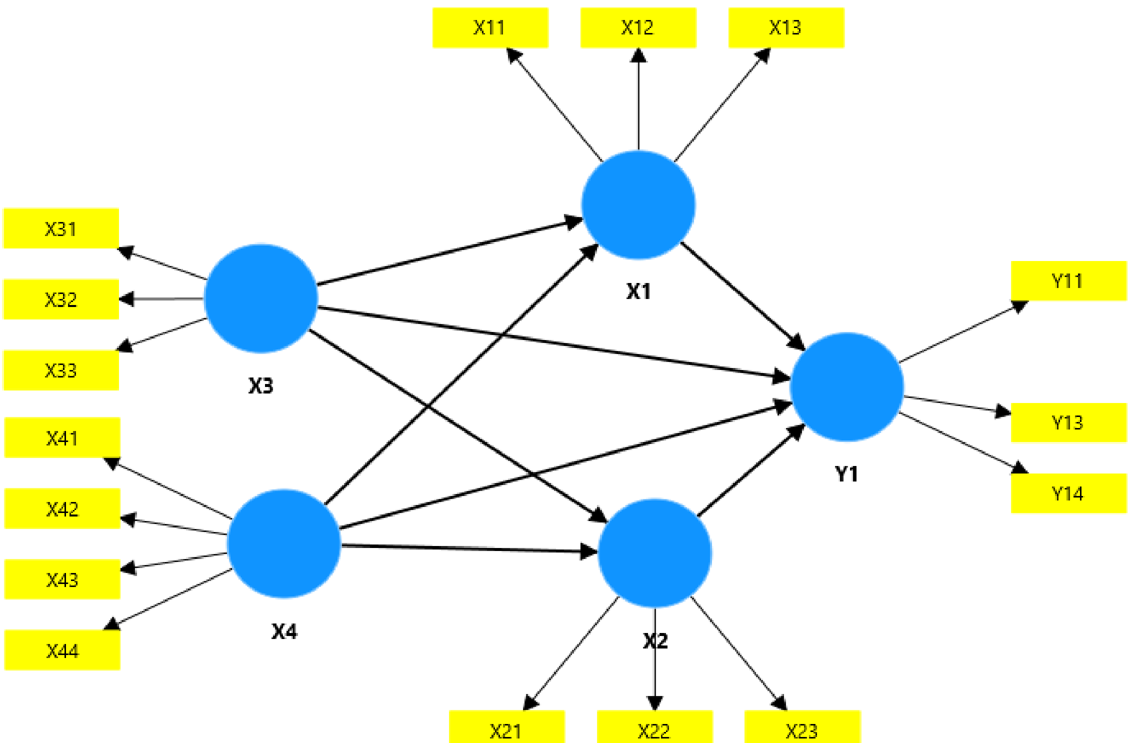

Figure 1. Causality model of independent variables with the financial performance of SMEs in agriculture

Figure 1 shows the correlation between endogenous variables (Y) and exogenous variables (X 1, 2). There is one endogenous variable and two exogenous variables. The model equation with the research path, the Equation for the Structural Model in Figure 1:

$$\eta = B\eta + \Gamma\xi + \zeta$$

Description:

η = This usually represents a particular variable or function in a given context, such as in a mathematical or physical model.

$B\eta$ = This shows that η is affected by the variable itself (multiplied by a constant B).

$\Gamma\xi$ = This shows the relationship between η and another variable (ξ), which is affected by a factor Γ.

ζ = This is a free term or disturbance that can affect the value of η but does not depend on η or ξ.

In other words, this equation states that the value of η is determined by a combination of its previous value ($B\eta$), the influence of the other variable ($\Gamma\xi$), and a disturbance or random variable (ζ).

3. Results and discussion

Analysis of data using SEM was used to identify factors that could affect the financial performance of MSMEs in the agricultural sector. To determine the values of the variables under study, each observed variable was first calculated based on its grouping in SEM, referred to as the loading factor value. The correlation value, derived from the analysis of the conceptual model, served as a benchmark for comparison. Convergent validity was tested using evaluation criteria for loading factors through a reflective process that involved eliminating indicators. Indicators with outer loading values ≥ 0.5 were retained, as shown in Table 3.

Table 2. Convergent validity

Variable	Path coefficients
X1 -> Y1	0,094
X2 -> Y1	0,252
X3 -> X1	0,202
X3 -> X2	0,074
X3 -> Y1	0,146
X4 -> X1	0,415
X4 -> X2	0,675
X4 -> Y1	0,416

Source: Primary Data Processing, 2024

The convergent validity results of SEM-PLS refer to the extent to which indicators of a latent variable are correlated with each other, indicating that they actually measure the same construct. Hair et al. [15] emphasized that convergent validity is an important prerequisite that shows that indicator variables have consistency in representing the same latent construct. In SEM-PLS, this is assessed through three main criteria.

According to Chin [14], the loading factor, or factor loading, represents the relationship of indicators with the latent variables it measures. A high loading factor (typically above 0.7) indicates that the indicator significantly contributes to the latent variable. However, Hair et al. [15], for exploratory research, a loading factor value of 0.6 was still considered acceptable. According to Puteh [16], The recommended minimum AVE value was 0.5. This value indicated that at least 50% of latent variables could explain different types of indicators, suggesting that the construct had adequate convergent validity [17]. It was also highlighted that AVE played a key role in ensuring the indicators effectively measured the same construct. Moreover, composite reliability (CR) served as an indicator of the internal consistency among variables measuring the same construct, similar to Cronbach's Alpha, but was more appropriate for SEM-PLS as it took into account the varying weights of indicators. A CR value exceeding 0.7 was considered to indicate strong reliability and support convergent validity. When convergent validity was high, it showed that the indicators accurately reflected the latent construct, making the model dependable. On the other hand, low convergent validity suggested that the indicators might not have been aligned or could have been measuring something unrelated to the intended latent variable, thus lowering the quality of the SEM-PLS analysis results. In general, this approach reinforced confidence in the idea that the indicators truly represented the latent constructs, which was vital for ensuring the accuracy and dependability of the SEM-PLS research outcomes.

Table 3. Composite reliability (CR) and Cronbach's alpha

Variable	Cronbach's alpha (c_a)	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
X1	0,975	0,976	0,983	0,952
X2	0,763	0,760	0,867	0,687
X3	0,596	0,605	0,775	0,536
X4	0,727	0,735	0,830	0,550
Y1	0,731	0,731	0,848	0,651

Source: Primary Data Processing, 2024

Table 1, the c_a and rho values for the technology-based acceleration program were significantly above 0.7, indicating that the technology-based acceleration program displayed very high reliability. This suggests that the indicators for technology-based acceleration programs were consistent and reliable in measuring the construct. Values exceeding 0.7 are generally considered a sign of good internal consistency, confirming that technology-based acceleration programs were effectively and accurately measuring the intended concept. This finding aligns with standard expectations for construct reliability in SEM-PLS, further validating the reliability of the measurement model for technology-based acceleration programs [15], which said that if the AVE value is above 0.7, it is considered good. The AVE of 0.952 also indicates that the indicator in the technology-based acceleration program construction has very high convergent validity, where more than 95% of the indicator's variance is explained by the latent variable.

Digital literacy with a c_a value of 0.763 and rho_c of 0.867 reliability was quite good and consistent. AVE 0.687 also meets the criteria [18]. It was recommended that a convergent validity value above 0.5 suggested that the indicators of digital literacy consistently represented the latent variable. UKM agriculture technology had a c_a value of 0.596, reflecting relatively low reliability, which might have indicated discrepancies among its indicators or potential issues with internal consistency. However, its composite reliability value of 0.775 was within acceptable limits, and the AVE of 0.536 met the minimum requirement, suggesting adequate convergent validity, though there was still potential to improve reliability. Government policy c_a and rho_a values of 0.727 and 0.830, respectively, indicated good reliability for the government policy construct.

Additionally, the AVE of 0.550 demonstrated sufficient convergent validity, meaning that over 50% of the variance in the indicators could be explained by the latent variable government policy. The financial performance of SMEs in the agricultural sector showed a c_a value of 0.731 and a rho_c of 0.848, reflecting solid reliability. The AVE of 0.651 indicated adequate convergent validity, meaning that the indicators of the financial performance of SMEs in the agricultural sector consistently measured the latent variable financial performance of SMEs in the agricultural sector. In conclusion, this study found that the technology-based acceleration program had the highest reliability and validity, meaning its indicators were highly consistent in measuring the construct. Digital literacy, government policy, and financial performance of SMEs in the agricultural sector also demonstrated good reliability and convergent validity, confirming that these constructs were reliable. However, UKM agriculture technology showed low reliability (c_a < 0.7), which suggested a need to reassess its indicators or add items to improve consistency. Overall, it can be concluded that most of the latent variable values can show consistency and validity of the data, except for the UKM agriculture technology variable, which needs further testing.

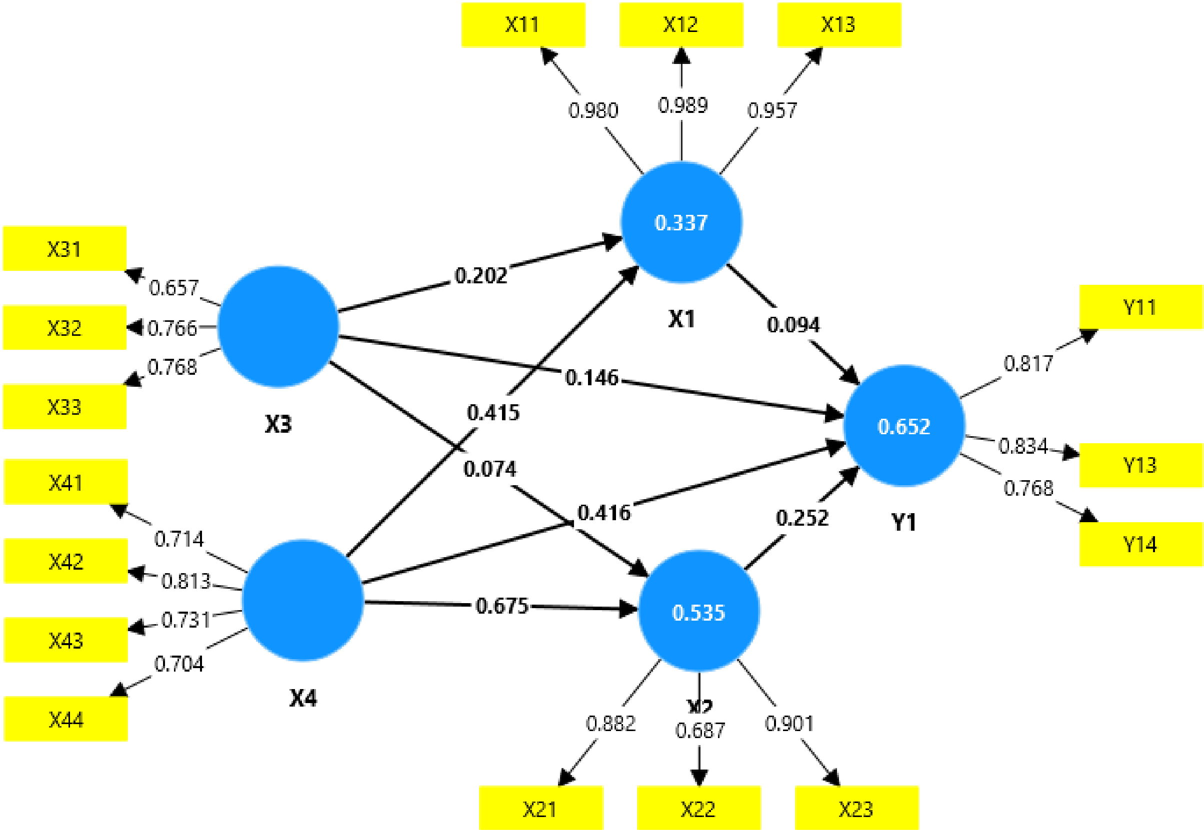

Figure 2. Path coefficient

Table 4. Path coefficient values and T-values

Variable	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
X1 -> Y1	0,094	0,106	0,154	0,611	0,541
X2 -> Y1	0,252	0,225	0,154	1,638	0,101
X3 -> X1	0,202	0,213	0,103	1,969	0,049
X3 -> X2	0,074	0,079	0,078	0,950	0,342
X3 -> Y1	0,146	0,146	0,098	1,480	0,139
X4 -> X1	0,415	0,421	0,093	4,452	0,000
X4 -> X2	0,675	0,688	0,067	10,137	0,000
X4 -> Y1	0,416	0,434	0,136	3,046	0,002

Source: Primary Data Processing, 2024

Based on the path coefficient values and T-values tables, the interpretation of the relationships between variables in the SEM-PLS model was as follows:

First, the technology-based acceleration program had a path coefficient of 0.094, indicating a very weak positive influence on the financial performance of SMEs in the agricultural sector. However, because the T-statistics value was 0.611 (below 1.96) and the p-value was 0.541 (above 0.05), this relationship was not statistically significant, meaning the technology-based acceleration program did not significantly affect the financial performance of SMEs in the agricultural sector.

Second, digital literacy had a path coefficient of 0.252, showing a moderate positive influence on the financial performance of SMEs in the agricultural sector. However, the T-statistics value of 1.638 was below the significance threshold of 1.96, and the p-value of 0.101 exceeded 0.05, so the effect of digital literacy on the financial performance of SMEs in the agricultural sector was not significant at the 5% significance level. This aligns with findings from [19], who also reported that the relationship between digital literacy and the financial performance of SMEs in the agricultural sector was not significant, pointing to possible mediating or moderating factors that were not captured in the model.

Third, UKM agriculture technology had a path coefficient of 0.202, with a T-statistics value of 1.969 (above 1.96) and a p-value of 0.049 (below 0.05), indicating that this relationship was statistically significant, showing that UKM agriculture technology had a positive and significant influence on technology-based acceleration program. This finding supports the work of those who suggested that UKM agriculture technology technological adoption) positively influenced technology-based acceleration programs [20][21] in their model, highlighting the importance of technological advancements in enhancing the performance of SMEs in the agricultural sector.

Fourth, UKM agriculture technology had a path coefficient of 0.074, indicating a very small positive influence on digital literacy, with a T-statistics value of 0.950 and a p-value of 0.342, neither of which met the significance criteria. Therefore, UKM agriculture technology did not significantly affect digital literacy. This result contrasts with [22], who found a stronger link between UKM agriculture technology and digital literacy, suggesting that the nature of the relationship might vary across different contexts or sectors.

Fifth, UKM agriculture technology had a path coefficient of 0.146, indicating a small positive effect on the financial performance of SMEs in the agricultural sector. However, because the T-statistics value of 1.480 and the p-value of 0.139 did not meet the significance threshold, this relationship was considered insignificant. This finding is somewhat at odds with [23], who reported that UKM agriculture technology had a significant effect on the financial performance of SMEs in the agricultural sector, possibly due to differences in the sample or measurement tools used.

Sixth, government policy had a path coefficient of 0.415, a T-statistics value of 4.452, and a p-value of 0.000, indicating a strong and statistically significant positive influence on the technology-based acceleration program. Seventh, government policy had a path coefficient of 0.675, showing a very strong influence on digital literacy, with a T-statistics value of 10.137 and a p-value of 0.000. This relationship was highly significant, indicating that government policy had a major influence on digital literacy. Eighth, government policy had a path coefficient of 0.416, indicating a significant positive influence on the financial performance of SMEs in the agricultural sector. With a T-statistics value of 3.046 and a p-value of 0.002, this relationship met the significance criteria, showing that government policy significantly influenced the financial performance of SMEs in the agricultural sector. According to [24], [25], which emphasized the importance of government policy (e.g., government policies or technological investments) in driving productivity and financial performance in agricultural SMEs.

Overall, government policy played an important role in influencing other variables (technology-based acceleration program, digital literacy, and financial performance of SMEs in the agricultural sector and had a significant impact on the financial performance of agricultural SMEs (financial performance of SMEs in the agricultural sector) in this model. This finding corroborates studies by [26] and [27], which highlighted the crucial role of government policy in enhancing the financial outcomes of SMEs in the agricultural sector. Meanwhile, UKM agriculture technology only had a significant effect on the technology-based acceleration program, with no significant impact on digital literacy or financial performance of SMEs in the agricultural

Sector. Additionally, technology-based acceleration programs and digital literacy did not significantly affect the financial performance of SMEs in the agricultural sector directly. This interpretation highlighted the importance of the factors represented by government policy in influencing the financial performance of agricultural SMEs, aligning with prior research that underscored the pivotal role of government policy's key factors in improving SME outcomes.

Table 5. SEM-PLS R-square output of agricultural SME financial performance

Indicator	R-square	R-square adjusted
X1	0,337	0,329
X2	0,535	0,529
Y1	0,652	0,643

Source: Primary Data Processing, 2024

Table 5 shows the output from the SEM-PLS model regarding the financial performance of agricultural SMEs. The technology-based acceleration program had an R-square value of 0.337, meaning that 33.7% of the variance could be explained by the exogenous variables in the model, while the remaining 66.3% was explained by factors outside the model. According to Kshetri [28], one of the external factors influencing technological acceleration is access to digital infrastructure, as well as overall government support. This suggests that external factors had a more dominant influence. The digital literacy variable had an R-square value of 0.535, indicating that 53.5% of the variance in digital literacy was explained by the variables in the model. Although this value was slightly higher than that of the acceleration program, it still did not significantly improve the explanation of digital literacy. Fundamental issues such as limited access to education and the influence of the local digital culture have not been addressed. According to Pynoo et al. [29], digital literacy among SMEs is usually influenced by education, openness to technology, and experience with technology. For the financial performance of SMEs in the agricultural sector, the R-square value of 0.652 indicated that 65.2% of the variance in financial performance was explained by the exogenous variables in the model, while the remaining 34.8% could be explained by variables outside the model. According to Akinboade and Kinfack [30], the financial performance of SMEs is more influenced by external factors, such as access to markets and local economic conditions.

4. Discussion

The independent variable affecting the financial performance of MSMEs in the agricultural sector is the technology-based acceleration program. Research has shown that these programs significantly contribute to improving the financial performance of agricultural MSMEs. By leveraging technology, these programs help MSMEs streamline operations, enhance productivity, and optimize resource management, which ultimately leads to increased profitability and financial growth. The integration of technological solutions within acceleration programs provides MSMEs with the tools and knowledge to adapt to modern agricultural practices, thus boosting their competitiveness in the market and supporting their overall financial success. This program involves various types of activities, such as mentoring, training, incubation, and funding, which help MSMEs overcome the challenges of technology adaptation.

The activities carried out are:

a) Division of program types: Acceleration programs involving training and incubation provide positive results in improving the technical and managerial skills of participants. Research by [31] and [32] states that this type of program facilitates MSMEs to improve their understanding of new technologies and better business strategies.

b) Program length duration: A longer duration allows MSMEs to absorb and apply the lessons learned, which is consistent with the findings of [33], which show that long-term acceleration programs have a positive impact on MSME growth.

c) Learning components: In the acceleration program, the components of digital literacy, product development, and entrepreneurship play a major role in preparing MSMEs to compete in the market. These results are supported by the study by [34], [35], which concluded that MSMEs that participate in programs with extensive learning components tend to experience improved financial and operational performance. Technology-based acceleration programs provide access to resources, training, and mentoring needed by agricultural MSMEs to adopt technology and improve management. Funding accessed through this acceleration program also helps MSMEs deal with capital constraints in developing their businesses. Support in the form of training and mentoring enables MSMEs to implement technology effectively, which increases their income and productivity [36].

Digital literacy was a significant factor in improving the financial performance of MSMEs, particularly in the use of applications and technology for agricultural land management. Mastery of smart farming applications allowed MSMEs to increase productivity through efficient and real-time monitoring, as highlighted by studies [37], [38], which demonstrated improved effectiveness in crop cultivation and maintenance. Additionally, the ability to analyze agronomic data, such as harvest results and soil quality, helped optimize agricultural yields, aligning with findings from [39] [40], which confirmed that data analysis directly enhanced productivity. Furthermore, innovative skills in utilizing agricultural technology strengthened MSMEs' market competitiveness, with [41] and [42] emphasizing that technology-based innovation boosted efficiency and competitive advantage. These digital literacy competencies enabled MSMEs to adopt new technologies, make informed decisions, and enhance productivity, ultimately leading to increased income and competitiveness.

Agricultural MSME technology, including smart farming, post-harvest innovations, and agricultural e-commerce, also played a vital role in improving financial performance. Smart farming automated agricultural processes, boosting production efficiency and reducing errors, as supported by [43]. Post-harvest technology extended product shelf life and maintained quality, increasing value and market prices, as noted by [43], which showed that smart farming plays an important role in cultivation efficiency. Post-harvest technology helps to increase the shelf life of the product and maintain post-harvest quality [44]. Agricultural e-commerce provided MSMEs with direct access to markets, reducing reliance on intermediaries and increasing profit margins, with [45] indicating that e-commerce enables MSMEs to reach a wider market and increase revenue. The use of technology in the agricultural process has a significant positive impact on the efficiency, productivity, and profitability of MSMEs. With smart farming, MSMEs can perform automatic monitoring that optimizes the agricultural process. Post-harvest technology and e-commerce add value to the product and expand market access, which directly contributes to improving the performance UMKM's financial performance.

Government policies in the form of financing, subsidies, training, and agricultural digitalization have a positive impact on the financial performance of UMKM:

a) Financing and credit access: This policy helps UMKM in obtaining capital to adopt new technologies. The study by [46] shows that credit access plays a significant role in supporting the growth of SMEs.
b) Subsidies and social assistance: Subsidies for technology enable UMKM to reduce initial costs, which increases the competitiveness of their products. Authors [47] emphasize that subsidies are very important to support technology adoption among small farmers.
c) Training and capacity development: Training provided by the government helps UMKM improve technical and managerial skills [48], revealing that continuous training has a positive impact on the skills and productivity of SMEs.
d) Agricultural digitalization: Digitalization allows faster access to information and connects with wider markets. According to [39], digitalization facilitates communication and data access, which helps

MSMEs in decision-making. Government policies that support technology adoption and capacity building in agricultural MSMEs are essential in strengthening competitiveness and productivity. Access to financing, subsidies, and training enhances MSMEs' ability to adopt technology, while digitalization enables better data management and wider market access. With supportive policies, MSMEs can reduce production costs, improve product quality, and achieve better financial results.

Overall, the study confirmed that technology-based acceleration programs, digital literacy, agricultural MSME technology, and government policies had a significant influence on the financial performance of agricultural MSMEs. These factors collectively enhanced productivity, expanded market access, and added value to agricultural products, leading to increased income, efficiency, and profitability in the agricultural sector.

The study's main novelty was its contribution to empirical evidence on the impact of acceleration programs and enhanced digital literacy on the financial performance of agricultural MSMEs. It quantitatively demonstrated how these factors improved income, business efficiency, and other financial performance aspects for MSMEs across South Sumatra Province. Furthermore, the study highlighted the positive effects of digital-based business incubation and mentoring programs, which significantly enhanced MSME financial outcomes in the agricultural sector. These findings enabled the development of recommendations for effective acceleration program models to support the digital transformation of agricultural MSMEs in various regions. Additionally, the research introduced innovations in designing digital literacy training models that improved small-scale farmers' knowledge and skills in adopting modern agricultural technologies, serving as potential benchmarks for creating farmer empowerment programs.

Based on the findings, several recommendations were proposed. These included improving MSME acceleration programs in the agricultural sector by incorporating digital literacy education and business digitalization support, making them more relevant to technological transformation needs. The development of online agricultural business incubation models was also suggested to increase commodity value addition through the involvement of rural youth, supported by funding and market access. Strengthening digital literacy training methods and curricula tailored for farmers, focusing on smart agricultural technologies, data-driven management, and digital marketing, was recommended. Fiscal incentives for industries to collaborate on agricultural technology solutions and advocacy for e-commerce regulations to enhance logistics for agricultural MSMEs were also emphasized. Finally, establishing special units within ministries or institutions to develop a national digital agricultural innovation ecosystem through multi-stakeholder collaboration was proposed to drive systemic change.

The limitations of this study that may be followed up in further research include geographical coverage since this study only focuses on agricultural MSMEs in South Sumatra, so the potential for generalizing the results to other regional and national contexts is limited. Although it covers the entire South Sumatra region, the selection of MSME samples is limited.

5. Conclusions

The analysis concluded that the independent variables of technology-based acceleration programs, digital literacy, MSMEs in the fields of agriculture, science, and technology, and policies taken by the government have a significant effect on the financial performance of agricultural MSMEs. The technology-based acceleration program proved to be essential by offering support through mentoring, training, incubation, and funding. The extended duration of the program and its varied learning components, such as digital literacy, agricultural product development, and entrepreneurship, improved the ability of agricultural MSMEs to adopt new technologies. The skills and knowledge gained from the program directly enhanced their financial performance by improving their competence in smart farming applications and their ability to analyze harvest data and soil quality. Moreover, the use of agricultural technology contributed to the competitiveness of agricultural MSMEs, resulting in increased income and productivity. The adoption of agricultural MSME technology, including smart farming, post-harvest technology, and e-commerce, positively influenced operational efficiency and market access.

These technologies facilitated higher harvest yields, better post-harvest management, and more effective marketing strategies. Government policies, such as financing, subsidies, training, and digitalization, played a significant role in supporting agricultural MSMEs. The availability of affordable credit and subsidies reduced the financial burdens, while training programs enhanced the skills and capacities of MSME owners and employees. Digitalization helped MSMEs access crucial information and markets, allowing them to make more informed decisions. Overall, the study demonstrated that effectively utilizing these variables enabled MSMEs to achieve sustainable growth, thereby contributing to both the agricultural sector and the broader economy. Future research was expected to examine the relationships between these variables more thoroughly, providing insights for the development of policies and programs that would further support agricultural MSMEs.

Declaration of competing interest

No conflict of interest in this study.

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Author contribution

Contribution LH: main idea, reviewer, data collector, supervisor, providing ideas, evaluating results, revising the manuscript. EP: writing, data collection, data analysis, Supervisor, reviewer, evaluator, creating concepts. TM: main idea, evaluation. AY: suggestions and evaluation of research results.

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