

Dynamic Capabilities and Firm Efficiency: A Study of Agro-Processing SMEs in Thailand

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Abstract

Dynamic Capabilities play an important role for organizations in the era of rapidly changing business environments, especially in the context of SMEs and industries facing high uncertainty such as agro-processing businesses in Thailand. Therefore, this study aims to explore the role of dynamic capabilities in terms of sensing, searching, seizing, shifting, and shaping in enhancing the performance of SMEs in the agro-processing sector in Thailand. The quantitative research approach was conducted by conducting an online survey with 645 SMEs in the agro-processing industry throughout Thailand, selected by stratified random sampling by the Department of Industry in Thailand. 250 correct answers were received within 90 days. The data were then analyzed using structural equation modeling (SEM) to analyze the path analysis to examine the relationship between dynamic capabilities and performance. The results of the study revealed that dynamic capabilities have both direct and indirect positive effects on performance through technological innovation ($p = 0.930$, $t = -3.064$) with a significance level of 0.01, which is a high level of impact, which is in line with the coping of agro-processing businesses in Thailand who are not ready to adapt due to many constraints. SMEs should focus on developing dynamic capabilities and adopting innovative practices to improve their company performance and market positioning for survival amidst intense competition. And most importantly, the government should promote the development of knowledge to keep up with rapidly changing situations and accelerate awareness of the importance of seizing opportunities to adapt them into strong corporate strategies, as well as support accessible sources of funding for sustainable future expansion.

Keywords: Dynamic Capabilities, Firm efficiency, Agro-Processing, SMEs, Thailand

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Introduction

Small and Medium Enterprises (SMEs) play a vital role in driving economic growth, fostering entrepreneurship, and promoting innovation. In Thailand, SMEs have become an essential force behind the nation's economic development, contributing significantly to the GDP and serving as a crucial mechanism for distributing economic benefits across the population. According to the World Bank Group (2025), economic growth in Thailand is projected to rise to 2.9 percent in 2025, up from 2.6 percent in 2024. In addition, the agricultural and agro-processing industries employ more than 40 percent of total employment. The introduction of AI and robotics technologies in this industry has the potential to increase production efficiency, reduce costs, and enhance competitiveness in the global market. However, despite their economic significance, many SMEs face persistent challenges, including limited access to financial resources, technological constraints, and a lack of strategic management capabilities. Without targeted interventions, these limitations could hinder their ability to remain competitive in an increasingly digital and globalized market.

To address these challenges, the concept of dynamic capabilities has emerged as a crucial theoretical framework in business strategy and organizational studies. Dynamic capabilities refer to an organization's ability to integrate, build, and reconfigure internal and external resources in response to changing environments (Teece et al., 1997). Over the past two decades, research on dynamic capabilities has expanded to explore their role in enabling firms to navigate technological disruptions, foster innovation, and achieve long-term competitive advantage. In the context of SMEs, scholars have increasingly emphasized the need to develop adaptive capabilities that allow small businesses to respond effectively to digital transformation and globalization. Given the unique constraints SMEs face—such as limited financial and human capital—understanding how they cultivate and deploy dynamic capabilities is essential for ensuring their sustainability and growth.

Among the various industries in which SMEs operate, the agro-processing sector holds particular importance. This industry plays a critical role in adding value to raw agricultural products, reducing post-harvest losses, and enhancing the competitiveness of Thailand's agricultural exports. Furthermore, agro-processing SMEs contribute significantly to rural employment and economic development by creating market opportunities for smallholder farmers. However, this sector also faces considerable challenges, including supply chain inefficiencies, quality control issues, and vulnerability to price fluctuations in global commodity markets. Given these structural complexities, understanding how SMEs in agro-processing can enhance their strategic adaptability and technological integration is crucial for sustaining their competitiveness.

A key driver of change in the agro-processing industry is the adoption of digital technologies. Innovations such as artificial intelligence (AI), robotics, blockchain, and the

Internet of Things (IoT) are transforming production processes, supply chain management, and quality assurance in the food and agriculture industries. These technologies offer a wide range of benefits, such as improved production efficiency, reduced costs, improved traceability, and better compliance with international safety and sustainability standards. For example, the use of AI-controlled robots in food and beverage production lines has reduced the need for manual labor and increased production consistency. In addition, the adoption of AI has enabled big data analytics to improve production processes and resource management in the agricultural sector (ETprotein, 2024). However, many SMEs struggle to adopt these advancements due to financial constraints, lack of skilled labor, and uncertainty about the return on investment. Without an effective strategy to integrate digital tools, agro-processing SMEs risk falling behind in an era where technological adaptation is a key factor in determining success.

Existing research on dynamic capabilities and digital transformation in SMEs has predominantly focused on sectors such as manufacturing, retail, and high-tech industries, while studies on agro-processing remain relatively limited. Some scholars have explored how SMEs leverage technology to improve supply chain resilience and product innovation, but few have examined the specific mechanisms through which dynamic capabilities enable digital adoption in resource-constrained settings. This gap presents an opportunity to investigate how agro-processing SMEs develop, reconfigure, and deploy their capabilities to navigate technological disruptions and market uncertainties. Addressing this gap will provide valuable insights into how SMEs in this sector can enhance their long-term sustainability through strategic technological adoption.

The insights gained from this study are expected to offer both academic and practical contributions. From a theoretical perspective, this research extends the understanding of how dynamic capabilities interact with technological adoption in resource-constrained environments. By integrating perspectives from strategic management and digital transformation, the study contributes to a more comprehensive framework for analyzing SME resilience and competitiveness. Practically, the findings aim to provide actionable recommendations for SMEs to enhance their operational efficiency and resilience. By addressing key barriers such as digital transformation readiness, financial constraints, and workforce skill gaps, this study seeks to equip SMEs in agro-processing with the strategies necessary to navigate an evolving global landscape.

Ultimately, strengthening this sector not only benefits individual enterprises but also contributes to Thailand's broader economic resilience and food security initiatives.

Objective

To examine the impact of dynamic capabilities (Sensing, Searching, Seizing, Shifting, Shaping) on financial, quality and marketing performance of agro-processing SMEs in Thailand.

Literature review

Dynamic capabilities

Organizational agility is the ability to adapt quickly, continuously and systematically in an evolving way. The 5s organizational agility in dynamic capabilities (Baškarada & Koronio, 2018) that support organizational agility that are suitable for SMEs in Thailand are as follows:

Sensing: Detecting opportunities and threats from external environments, such as demand for health products, impacts from bans on imports of products from Japan, or PM2.5 dust problems affecting agricultural production.

Searching: Finding new opportunities within the organization, such as adapting to growing market trends, such as producing environmentally friendly products or healthy food.

Seizing: Deciding on new strategies and business models, such as expanding online sales channels or forming partnerships with influencers in the health food market.

Shifting: Changing strategies and business models, such as using online marketing or changing production processes to meet new consumer demands.

Shaping: Creating impacts on external environments, such as expanding production to support health food trends and supporting changes in consumer behavior in the new era.

Technological innovations

Technological innovation plays a key role in the development of agricultural processing SMEs by increasing efficiency and reducing costs, such as the use of drones in agriculture, smart greenhouses to control the cultivation environment, the use of AI to inspect product quality, online platforms for agricultural marketing, and smart agricultural tools that reduce labor and facilitate production. These technologies not only increase productivity and quality, but also help create market differentiation and increase the value of agricultural processing SMEs' products.

There are four main types of technological innovation through the application of digital technology to the agro-processing business: product innovation, process innovation, business model innovation, and social innovation. (Battisti et al., 2022; Akter et al., 2021; Mishra & Tripathi, 2021; Agostini & Filippini, 2019)

1) Product innovation: In R&D, the adoption of digital technologies enables businesses to support strategic marketing activities. including understanding the market potential for new products/services

2) Process innovation: The use of digital technologies enhances a company's ability to restructure and reengineer processes for process innovation

3) Business model innovation: Many successful organizations have embraced digital technologies in their operations and developed unique AI-based business models. Companies that successfully integrate digital technologies into their business and operations models can unleash disruptive innovations that transform the entire value chain. In addition, to improve the value proposition, companies need to embrace changes in one dimension (value creation, value appropriation, or value delivery), resulting in business model innovation.

4) Social innovation: Social innovation initiatives – typically launched to develop products and services that meet social needs– have emerged as an alternative approach to co-creating innovations and sustainable solutions to new and complex social and economic problems. AI-driven platforms are a reliable alternative for addressing key social issues, to stimulate economic growth and improve people's lives , positively impacting individuals, businesses, and society. In addition, social innovation initiatives help businesses create social value by developing environmental, social, and economic initiatives to generate social innovations.

Firm efficiency

Overall, a company's performance is a long-term opportunity for improving financial stability, customer retention, effective risk management, and continuous adaptation to a changing business environment (Marsick & Watkins, 2003). Business owners and managers often strive to ensure that their operations are as efficient as possible. Business performance is defined as “the ability to operate effectively, profitably, survive, grow, and respond to environmental opportunities and threats” (Fernando et al, 2019). Liu et al. (2021) similarly emphasize that digital technologies enable businesses to expand without incurring additional costs. Pizzi et al. (2021) further state that companies can address shortcomings, increase efficiency, add new functions throughout the product lifecycle, promote innovation through digital technologies, and significantly improve their innovation capabilities.

The benefits of SMEs can be measured through financial and non-financial metrics. Financial measures include indicators of financial efficiency, such as sales and profit growth, operating costs, and the adoption of cutting-edge technologies within supply chain transformation processes, as well as market share. Non-financial measures include production efficiency, such as production quality, economies of scale, delivery time to customers, and production flexibility. Marketing efficiency, which this research uses as an indicator of firm efficiency, aligns with the findings of Kaynak et al. (2013).

Overall, organizational efficiency should be evaluated through various operational efficiencies, including financial efficiency, quality efficiency, and marketing efficiency.

Dynamic capabilities and technological innovations impact to Firm efficiency

A review of the relationship between dynamic capabilities of agribusiness enterprises and organizational performance found both supportive and conflicting views. Research from 2023-2025 indicates that organizations that develop capabilities in big data analytics, blockchain technology, open innovation, and artificial intelligence tend to have higher operational performance (Kumar et al., 2023; Kava et al., 2024). However, conflicting research suggests that overinvesting in dynamic capabilities may not be worthwhile, especially for SMEs (Battaglia & Neirotti., 2022), and may lead organizations to neglect developing core capabilities and long-term relationships with stakeholders (Szczepanska-Woszczyna & Muras, 2023; Guo et al., 2022). Therefore, such a relationship is complex and depends on many factors, such as business size, market context, and the ability to balance innovation development with maintaining core business expertise. Successful organizations tend to be able to manage their resources effectively. and can assess the value of investing in developing dynamic capabilities that are appropriate to the context and available resources (Tanwar et al., 2023).

In addition, there is also research from Thailand by Chumphong et al. (2020) was found that SMEs can increase their competitiveness in a globalized economy by adapting to rapid changes. In line with Mongkol (2023) Thailand's robotics and artificial intelligence skills are increasing rapidly due to their relevance to the global supply chain and the improvements brought about by the coronavirus pandemic and global trends. The Thai government has introduced AI into the national development plan and national policy. Thailand 4.0 places great importance on AI, robotics and digital industries. Since AI has a significant impact on digital transactions and economic growth in Thailand, the Thai government must anticipate future progress, especially in the AI industry, in order to effectively respond to the volatile and uncertain future. Lalaeng (2024) found important research results revealing that the structural model is consistent with empirical data. The green economy, market efficiency and competitive advantage all have a significant positive impact on business performance. Further analysis shows that the green economy has a direct influence on market pressure and competitive advantage. In addition, the study also identified a direct positive relationship between market pressure, green dynamic capabilities. and socially responsible leadership with a green economy.

However, this research has not yet studied the agricultural product processing business in Thailand. Therefore, the researcher is interested in studying the dynamic potential that affects the efficiency of the organization to what extent for medium and small-sized enterprises that will be able to compete in the fiercely competitive market from gaining competitive advantages in various factors.

Methodology

This study employed a quantitative research design to investigate the impact of dynamic capabilities and technological innovations on firm efficiency among SMEs in the agricultural processing industry in Thailand.

1. Population and Sampling

- **Target Population:** The study targeted 645 SMEs in the agro-processing industry in Thailand. These SMEs were selected based on the criterion that their revenue did not exceed 500 million baht. (DBD Datawarehouse, 2024)
- **Sampling Technique:** The sample group used in this research is the cluster sampling method by selecting agricultural businesses that process vegetables and fruits in the manufacturing industry with the following conditions:
 - The business must be registered according to the Industrial Standards (Thailand) 2009 and operate in the processed agricultural product group.
 - It is classified according to the manufacturing industry category C, code 103, because it is specifically for vegetables and fruits.
 - Then, only small businesses (S) and medium-sized businesses (M) with total annual revenue of 1 - 500 million baht were selected according to the criteria for grouping business sizes from total revenue of the Department of Business Development (2024) to confirm the appropriate income for using digital technology.
- **Response Rate:** Out of the 645 SMEs approached, 250 responded, resulting in a response rate of 38.75%. This sample size was deemed sufficient for the statistical analysis employed in the study.

2. Data Collection

- **Data collection method:** The survey was conducted using an online questionnaire distributed via email to a target group of 645 businesses, one owner or representative per business.
- **Survey instrument:** The questionnaire was structured with Likert-type questions assessing the dynamic capabilities, adoption of technological innovation, and performance indicators of the companies.

3. Variables and Measurement

Independent Variables:

- **Dynamic Capabilities:** This includes the firm's ability to sensing, searching, seizing, shifting and shaping.
- **Technological Innovations:** The level of adoption of new technologies in an organization's processes includes product innovation, process innovation, business model innovation, and social innovation.

- **Dependent Variable:**

- **Firm Performance:** Measured using indicators such as Financial efficiency, Quality efficiency and Marketing efficiency.

The researcher created a questionnaire instrument from the established research framework and operational definitions to obtain data on the opinions of business executives or managers using a 5-level rating scale: the most, much, moderate, little, and least. It consists of 4 parts:

Part 1: General information about the company.

Part 2: The company's dynamic capability in using digital technology in agricultural product processing.

Part 3: Creating technological innovations in agricultural product processing; and

Part 4: The company's efficiency resulting from using digital technology in agricultural product processing.

The quality of the instrument was then examined in terms of content validity of the questionnaire and interview form. From the evaluation by 3 experts on the use of technology in agricultural processing businesses, it was found that the index of consistency of each question was 0.73, which is between 0.60-1.00, indicating that the research instrument passed the acceptance criteria. As for the questions with an IOC value lower than 0.50, they were revised, or some questions were eliminated due to lack of content validity.

4. Data Analysis

- Statistical Technique: This study used Causal Model Analysis through Structural Equation Modeling (SEM) to test the causal relationship among relevant variables: dynamic capabilities, technological innovation, and performance of small and medium-sized agro-processing businesses in Thailand. SPSS was used with JASP, a statistical analysis software capable of efficiently processing Bayesian and Frequentist SEM, using Path Analysis.

- Software: Ready-made statistical software programs are used to perform structural equation analysis.

5. Ethical Considerations

- The research project number is P2-0180/2023.
- Informed Consent: Participants were informed about the purpose of the study and consented to participate voluntarily.
- Confidentiality: Measures were taken to ensure that the data collected was kept confidential and used solely for research purposes.

This methodology provided a robust framework for understanding the impact of dynamic capabilities and technological innovations on the efficiency and overall performance of agro-processing SMEs in Thailand. The use of hierarchical stepwise regression analysis enabled the researchers to identify key factors that contribute to firm efficiency, offering valuable insights for both practitioners and policymakers in the agricultural processing sector.

Results

Agro-Processing SMEs in Thailand

The analysis results from 250 people found that most of the respondents were limited companies, 170 companies, or 68 percent. Most of them had been in business for 5 years or more, 222 companies, or 88.88 percent. In terms of the number of employees in the company, most of them had less than or equal to 10 employees, 103 companies, or 41.20 percent. Next, the local vegetable and fruit raw materials that the company processed, most of them were rice, 63 companies, or 25.20 percent. In terms of the product processing process, most of them were deep-fried, 77 companies, or 30.80 percent. And in terms of using digital technology in the processing process, most of them used semi-automatic machines, 152 companies, or 60.80 percent.

The overall view of the level of opinion on the influence of dynamic capabilities using digital technology on the efficiency of agro-processing businesses was at the highest level overall, with an average of 4.50. When considering each aspect, it was found that the aspect with the highest average was dynamic capabilities in using technology, with an average of 4.59, followed by the efficiency of SMEs, with an average of 4.45, and technological innovation had an average of 4.43, respectively. As shown in Table 1.

Table 1 The Summary of the Overall Level of Opinions on the Influence of Dynamic Capabilities Using Digital Technologies on Firm Efficiency.

Variable	$\bar{X}$	S.D	Opinion level
Dynamic Capabilities	4.53	0.411	Strongly Agree
1.1 Sensing	4.60	0.402	Strongly Agree
1.2 Searching	4.55	0.493	Strongly Agree
1.3 Siezing	4.48	0.464	Strongly Agree
1.4 Shifting	4.50	0.472	Strongly Agree
1.5 Shaping	4.53	0.429	Strongly Agree
Technological innovations	4.44	0.558	Strongly Agree
2.1 Product innovation	4.40	0.576	Strongly Agree
2.2 Process innovation	4.58	0.583	Strongly Agree
2.3 Business Model innovation	4.33	0.463	Strongly Agree
2.4 Social innovation	4.43	0.681	Strongly Agree
Firm efficiency	4.50	0.400	Strongly Agree
2.1 Financial	4.51	0.627	Strongly Agree
2.2 Quality	4.47	0.483	Strongly Agree
2.3 Marketing	4.50	0.542	Strongly Agree
Total	4.50	0.456	Strongly Agree

* The Likert-type evaluation is divided into 5 levels.

Examination of the distribution of observed variables studied in the model

When considering the distribution coefficient C.V. (%), it was found that all variables had a distribution of data that was not very different, which was between 6.95 and 18.00 percent, with the variable with the least distribution being SEN1 (Business knows the best processing methods in the processed agricultural product market) (6.95 percent).

When considering the skewness or asymmetry of the distribution, it was found that most variables had a slightly left-skewed distribution (negative skewness), indicating that the data of these variables had mostly higher scores than the average.

When considering the kurtosis or height of the distribution, it was found that most variables had a distribution curve that was shorter and flatter than normal (negative kurtosis), indicating that the data of the observed variables had a lot of data distribution.

Correlation Analysis

Various dynamic capabilities such as SENS (Sensing), SIEZ (Seizing), and others were analyzed for their correlations. As shown in Table 2.

Table 2 Summarizing the Relationships Among the Dynamic Capabilities

	SEN	SEAR	SEI	SHIF	SHAP	PROD	PROC	BUSI	SOCI	FIN	QUA	MKT
SEN	1											
SEAR	.785**	1										
SEI	.866**	.747**	1									
SHIF	.756**	.696**	.736**	1								
SHAP	.888**	.859**	.790**	.760**	1							
PROD	.742**	.683**	.716**	.612**	.697**	1						
PROC	.836**	.716**	.763**	.679**	.852**	.703**	1					
BUSI	.653**	.389**	.552**	.558**	.580**	.649**	.663**	1				
SOCI	.460**	.445**	.510**	.363**	.522**	.311**	.451**	.283**	1			
FIN	.212**	.094	.259**	.027	.111	.449**	.207**	.348**	.183**	1		
QUA	.448**	.485**	.390**	.527**	.583**	.396**	.425**	.509**	.399**	.176**	1	
MKT	.029	.089	.070	.054	.065	.176**	.118	.182**	.032	.384**	.211**	1

Significant at the 0.01 level (2-tailed)

The results of the analysis of the relationship between all 12 observed variables used in the research were shown. The results of the analysis of the relationship between

66 pairs of variables showed that 5 pairs had a statistically significant relationship at the .01 level and 51 pairs had a statistically significant relationship at the .001 level. The correlation coefficients between the variables were all positive, ranging from 0.176 to 0.888. The researcher used all the observed variables in the data analysis because each pair of variables had a linear relationship in the positive direction and did not have multicollinearity (the r value in the correlation matrix exceeded 0.90).

The statistical value of the relationship between observed variables

By the criteria, Kaiser-Meyer-Olkin (KMO) value > 0.60 is considered suitable for factor analysis (Kaiser, 1974). Bartlett's Test value should have $p < 0.05$ to confirm that the variables are sufficiently related for Factor Analysis.

Table 3 Shows the Statistical Values to Test the Relationship Between Observed Variables.

Test statistics			Obtained test statistics	Result
Bartlett's Test			2595.985	Reject H_0
Kaiser-Meyer-Olkin	Measure	of	0.873	More than 0.8
Sampling Adequacy (KMO)				approaching 1

From the table, it was found that the KMO (Kaiser-Meyer-Olkin) value, which is a measure of the appropriateness (Adequacy) of the data in the factor analysis, was equal to 0.873, which is greater than 0.8 and close to 1. In conclusion, this data set is appropriate for using the factor analysis technique.

For the Bartlett's Test of Sphericity, the following hypotheses were set:

H_0 : The 12 variables (A1, A2,...A12) are not related to each other.

H_1 : The 12 variables (A1, A2,...A12) are related to each other.

From the table, the test statistic value (Chi-Square) was equal to 2595.985 and the p -value was equal to .000, indicating that the 12 variables are related to each other. Therefore, it is appropriate to use the factor analysis technique.

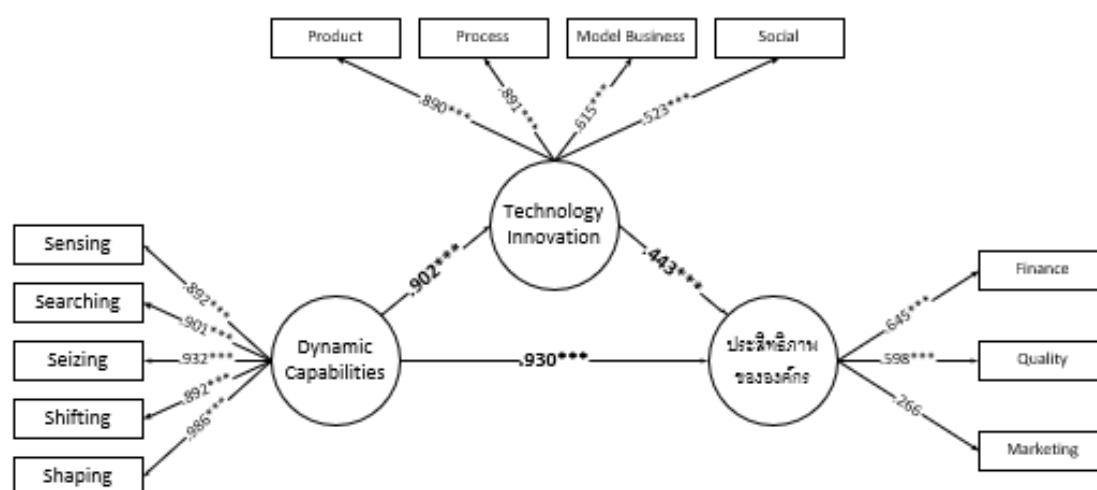
Results of the analysis of the consistency of the causal relationship model

The fit index of the covariance matrix of the samples obtained from the data of the causal relationship model of factors affecting the performance of medium and small-sized agro-processing businesses in Thailand, which is the hypothetical model, is compared with the final model that has been adjusted to be consistent with the empirical data based on the theoretical rationale studied together with the model fit index recommended by the program, as shown in Table 4 and Figure 1.

Table 4 Results of the Analysis of the Consistency of the Hypothesized Model with Empirical Data

Index value	Criteria	Before model adjustment	After model adjustment
Loglikelihood Ratio Chi-Square Statistic χ^2	-	521.312	106.236
Degrees of Freedom (df)	-	54	36
P-Value	>0.05	.000	.000
Relative Chi-Square Value (χ^2/df)	< 5	9.654	2.951
Comparative fit index (CFI)	>0.90	.819	.973
Tucker-Lewis Index (TLI)	>0.90	.779	.950
Goodness of Fit Index (GFI)	>0.90	.759	.944
Root Mean Square Error of Approximation (RMSEA)	<0.10	.186	.089
Standard Root Mean Square Residual (SRMR)	<0.05	.025	0.12

It was found that after adjusting the model, all values met the specified criteria. The summary is as follows: $\chi^2 = 71.197$, $\text{df} = 50$, $\chi^2/\text{df} = 1.424$, $p\text{-value} = 0.026$, $\text{CFI} = 0.996$, $\text{TLI} = 0.992$, $\text{RMSEA} = 0.035$, $\text{SRMR} = 0.020$

**Figure 1** Results of the Validity Test of the Research Hypothesis Model after Model Adjustment.

When considering the total effect (TE) on organizational performance (FE), it was found that the organizational performance (FE) variable was influenced by the internal latent variable, Technological Innovation (TIN), with an influence size of 0.443, statistically significant at the .001 level, which was both directly and positively influenced by the influence size of 0.443.

The organizational performance (FE) variable was directly influenced by the external latent variable, Dynamic Capability (DC), with an influencing size of 0.930, statistically significant at the .001 level, with a direct and positive influence of 0.317, and an indirect and positive influence of 0.623, statistically significant at the .01 level.

The external latent variable, Dynamic Capability (DC), had a direct and positive influence on the internal latent variable, Technological Innovation (TIN), with an influence size of 0.902, statistically significant at the .001 level.

In addition, the coefficient of determination (R^2) of the latent variable in technological innovation (TIN) accounts for approximately 72.9 percent of the variance in the latent variable that is explained by the independent variables in the structural equation, while the organizational performance (FE) variable accounts for only approximately 26.6 percent of the variance in the latent variable that is explained by the independent variables in the structural equation.

The results of hypothesis testing of the causal relationship model of factors influencing the performance of medium and small-scale agro-processing businesses in Thailand, which were constructed with empirical data, can be summarized as follows.

Table 5 Results of Research Hypothesis Testing

	Research hypothesis	Path coefficient	t	Hypothesis testing results
1	Dynamic capabilities have a direct positive effect on technological innovation of agro-processing businesses.	0.902	25.900***	Support the hypothesis
2	Technological innovation has a direct and positive impact on the performance of agro-processing businesses.	0.443	8.821***	Support the hypothesis
3	Dynamic capabilities have direct and indirect positive effects on the performance of agro-processing businesses in contrast.	0.930	-3.064**	Support the hypothesis

The results of the research hypothesis testing support all four hypotheses, which answers the research objective: To examine the impact of dynamic capabilities (Sensing, Searching, Seizing, Shifting, Shaping) on financial, quality and marketing performance of agro-processing SMEs in Thailand. This has both direct and indirect positive effects.

Discussion

Dynamic capabilities have direct and indirect positive effects on the performance of agro-processing businesses in contrast. The direct impact is that the development of dynamic capabilities directly affects the operations and profits of the business, such as increasing productivity, reducing costs, and improving product quality. This is consistent with the research of Singh et al. (2023) that found that the dynamic capabilities of agro-processing businesses have a direct and positive impact on the organization's financial performance, which was found to increase profit margins and returns on investment.

However, rapid strategy changes can lead to higher operating costs and financial uncertainty (Chen et al., 2023). Therefore, careful management planning and funding sources must be sought to support the adoption of technologies to enhance the organization's capabilities in the future.

The indirect impact is that dynamic capabilities help enhance long-term competitiveness, allowing businesses to build good relationships with partners, expand markets, and increase opportunities for sustainable growth. This is consistent with the research of Sharma & Kumar (2024) that found that marketing efficiency helps increase market share and customer satisfaction for the organization. And help organizations adapt to environmental and social changes (Nguyen et al., 2024). Recent studies also confirm that these positive impacts are particularly important in the context of rapidly changing and intensely competitive markets in the agro-processing sector (Zhou & Li, 2022). However, research suggests that despite the importance of dynamic capabilities, if they are not properly planned and managed, they can have a negative impact on organizational performance (Zhang et al., 2024).

Therefore, putting customers at the center of innovation will enable agro-processing businesses to compete in the intense market and survive in the long run by using digital technologies to create this advantage. The government must support easily accessible sources of funding for sustainable growth in the future.

Suggestion

Suggestions for applying research results

1) Theoretical Utilization

Further study on dynamic capabilities in the context of SMEs in Thailand can help strengthen the theoretical framework on business adaptation and transformation in a rapidly changing environment. By studying the relationship between dynamic capabilities, technological innovation, and operational performance, it can help expand the scope of relevant theories in strategic management and business adaptation.

2) Practical Utilization

SMEs in Thailand should develop dynamic capabilities to enhance their competitiveness through the development and adoption of new technologies in production and operations. Investing in innovation and employee training can help these businesses adapt faster to changes in the market and technology. Building these capabilities will improve production efficiency and reduce costs.

An example of a processing business that has successfully applied technology to its processing is Siam Coconut, a coconut product manufacturer that uses technology to process coconuts into a variety of products, such as coconut water and coconut milk, by using automation in the production process and processing technology to extend the

shelf life of the products. This use of technology helps reduce production costs and enables the production of products with consistent quality.

The factors that influenced the success of using technology in agricultural processing in the case study can be linked to Dynamic Capabilities, which consist of several important aspects, such as:

Sensing: The ability to quickly identify and detect new technological opportunities or trends in the market is a key success factor, such as in the case of Siam Coconut, which was able to identify opportunities to use processing technologies that improve the quality and shelf life of coconut products, or in the case of farmers in the Smart Farm project, who were able to detect water and nutrient requirements appropriately through sensor technology.

Searching: The ability to search for new knowledge and technologies. That can be applied in product and production process development, such as Thai Beverage, which uses research and development (R&D) to find efficient production methods that are in line with consumer market trends.

Seizing (Seizing opportunities)

The ability to make decisions quickly and use discovered technological opportunities to develop and improve production processes, such as Siam Coconut, which can apply new technologies to coconut processing and improve product quality in foreign markets.

Shifting (Changing processes or strategies)

The ability to adjust strategies and production processes to suit changes in the market or technology, such as Thai Beverage, which has adjusted its production and marketing processes to suit changes in the rapidly growing beverage market.

Shaping (Creating an environment and networking)

Creating an environment conducive to technology development and application in the organization, including networking with partners, such as collaborating with research institutes or technology companies to develop new innovations, as can be seen in the Smart Farm project, which connects farmers and agricultural technology through networking between the public and private sectors.

3) Policy Utilization

For the government, it should support the development of dynamic capabilities in SMEs through supportive policies, such as helping research and development (R&D) and financial support for investment in technological innovation. In addition, the establishment of collaborative networks between SMEs, universities, and research institutes should be promoted to facilitate the exchange of knowledge and technologies that are beneficial to business development in the long term.

An example of a project in Thailand is the Smart Farm project, which has promoted the introduction of technologies to assist in farm management, such as sensor

systems to measure soil moisture and temperature, automatic watering systems, and the use of satellite data to monitor plant growth conditions. These technologies help farmers increase yields and reduce unnecessary resource use, resulting in more efficient and better-quality farm produce processing.

There are several factors that affect the success of a Smart Farm project or a project that uses technology to manage a farm, such as:

Public-private partnership: Partnerships between the government, technology companies, and farmers are a key factor in driving the adoption of technology in the agricultural sector. Government support, such as financial support programs, consulting, or infrastructure development, can help reduce barriers to technology adoption.

Training and knowledge development: Training farmers to understand the use of new technologies, such as sensor systems and satellite data, is essential to enabling farmers to use these technologies effectively. Developing skills in using new tools increases confidence in operations and makes production more efficient.

Access to technology and data: Access to technology and data from various sources, such as weather data from satellites or online farm management platforms that collect data for accurate decision-making, is essential to increase agricultural efficiency. The development of infrastructure and systems that can quickly connect data is essential.

Resource management: Efficient management of resources, such as water, fertilizer, and energy, using control and monitoring technologies, such as automatic watering systems, can reduce resource loss and lower production costs.

Networking and collaboration: Networking between farmers, researchers, and technology companies allows for the exchange of knowledge and experiences in using new technologies. Collaboration in a community setting helps spread knowledge and create sustainability in the project.

Suggestions for future research or further research

1) Exploring the Role of External Factors

Future research could explore how external factors, such as government policies, market conditions, and global trends, influence the relationship between dynamic capabilities and performance in agricultural processing SMEs in Thailand. This would help identify the broader context in which dynamic capabilities are most effective.

2) Impact of Digital Transformation and Technological Innovation

Further research could investigate the specific role of digital transformation and emerging technologies (e.g., AI, automation) in enhancing dynamic capabilities within agricultural processing businesses. Understanding the mechanisms through which these technologies contribute to operational efficiency and competitiveness could offer valuable insights.

3) Comparative Studies Across Regions or Industries

Comparative research across different regions or industries could provide a deeper understanding of how dynamic capabilities operate in various contexts. This would allow for the identification of industry-specific or region-specific factors that either enhance or hinder the effectiveness of dynamic capabilities in SMEs.

Limitations of the research

1) Context-Specific Limitations

The research primarily focuses on agricultural processing SMEs in Thailand, which may limit the generalizability of the findings to other industries or regions. Differences in economic conditions, infrastructure, and market dynamics may affect how dynamic capabilities impact business performance in other contexts.

2) Data Collection Constraints

The study may have relied on a limited sample size or specific data collection methods, such as surveys or interviews, which could introduce biases or incomplete representation of the broader population of agricultural SMEs. This might affect the robustness and comprehensiveness of the findings.

3) Causal Inference Limitations

While the research identifies correlations between dynamic capabilities and business performance, establishing a clear causal relationship remains challenging. The study may not have fully accounted for all possible mediating or moderating variables that could influence the outcomes, thus limiting the ability to make definitive causal claims.

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