DETERMINANTS OF AI-BASED APPLICATIONS ADOPTION IN THE AGRICULTURAL SECTOR – MULTI-GROUP ANALYSIS
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ปัจจัยกำหนดการนำแอปพลิเคชันที่ใช้ AI มาใช้ในภาคเกษตรกรรม – การวิเคราะห์แบบหลายกลุ่ม

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DOI: https://doi.org/10.35633/inmateh-72-67

***Keywords:** AI-based application, agricultural sector, artificial intelligence, organizational size, managerial support, technological competence*

ABSTRACT
This research investigated the factors determining the adoption of AI-based applications in Thailand and Poland's agricultural sectors. The study explored the sector's adoption of AI technology and its contributions to driving the market and business performance. Despite the potential of AI in the agricultural sector, its adoption rate still needs to be clarified, and its potential needs to be better understood, hence the need for the study. The research applied primary data collected from respondents working in the agricultural sector in Thailand and Poland using a structured questionnaire. A sample of 356 and 377 respondents were representative samples in Thailand and Poland, respectively. The research was driven by the hypotheses evaluated using the Structural Equation Model (SEM). The findings indicated that organizational size was the most influential determinant of AI-based applications in both countries. Another significant determinant was technological competence in both countries. Additionally, social influence was a significant determinant in Thailand, while facilitating conditions and effort expectancy were significant determinants in Poland. The multi-group analysis revealed that the two countries were not invariant; hence, the effect of independent variables on behavioral intention to adopt AI between the two countries was different. The research recommended that each country's policymakers consider its contexts differently in AI-based application adoption policies. However, improving the organizational size and technological competence would enhance the adoption of AI-based applications across the board.

INTRODUCTION
Artificial Intelligence (AI) has seen many developments recently, with the technology adopted in various industries to improve business processes and outcomes. The potential of AI in transforming businesses cannot be overstated, and its applications continue to expand, ranging from customer service to healthcare, finance, transportation, and agriculture. According to a report by *Grand View Research (2023),* in 2022, the size of the artificial intelligence market worldwide reached USD 136.55 billion and is expected to grow at an annual compound rate of 37.3% from 2023 to 2030. The report also states that the increasing adoption of AI technologies in various industries is one of the major factors driving market growth. The widespread adoption of AI is mainly due to its ability to solve complex business problems, leading to increased productivity, efficiency, and profitability (*Ayub Khan et al., 2022; Regona et al., 2022; Vinuesa et al., 2020*).

Artificial Intelligence (AI) is transforming the agricultural industry worldwide, significantly improving the efficiency and productivity of farming practices. *Van Hilten and Wolfert (2022)* inform that the AI revolution is fueled by a continual technical innovation that increases networking capability with the possibility of running tractors, spraying drones, and completely autonomous robotic farms, all probable results of AI innovation in the agricultural industry. The study by Vantage Market Research (2023) estimates that AI in the agriculture market is predicted to grow at a CAGR of 25.1% during the forecast period, reaching $4.2 billion by 2028 from $1.1 billion in 2022. The report notes that the increasing demand for food and the rising adoption of innovative farming practices are the key drivers of the growth of AI in the agriculture market. *Srivetbodee and Igel (2021)* aver that AI can help farmers optimize crop yields, reduce waste, and improve product quality while

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understanding that sustainability is vital in agriculture and continuous food availability (*Nuanphromsakul et al., 2022; Ndinojuo, 2020; Wolfert & Isakhanyan, 2022*). Srivetbodee and Igel (2021) continue that AI has been effective in helping farmers predict weather patterns, monitor soil conditions, and detect crop diseases.

In Thailand, the agricultural sector is one of the main contributors to the country's economy. According to *Statista Research Department (2022),* Thailand's agriculture, hunting, and forestry industry made a GDP contribution of around 1.38 trillion Thai baht in 2021. In Poland, the agricultural sector is also a vital part of the economy, contributing by approximately 2.22 percent to the country's GDP in 2021 (*O'Neill, 2021*). The Thailand and Poland governments support AI development in agriculture, focusing on improving the sector's efficiency and competitiveness. Both governments have been actively promoting technology in agriculture, focusing on AI, autonomous, and precision farming.

The adoption of precision farming in Thailand is still in its early stages, with only a few large-scale farms and research institutions implementing the technology. Precision farming uses data analytics, machine learning, and sensors to optimize crop yields and reduce waste (*Srivetbodee & Igel, 2021*). In Poland, precision farming is more widespread, with many farmers adopting the technology to optimize crop yields and reduce costs (*Yarashynskaya & Prus, 2022*). The adoption of autonomous farming is still in its early stages in Thailand and Poland, with only a few large-scale farms and research institutions implementing the technology (*Kernecker et al., 2020; Chaveesuk et al., 2023*). *Chaveesuk et al. (2023)* infer that autonomous farming involves using robotics and AI to automate farming processes, such as planting, harvesting, and weeding. AI is poised to affect the agricultural sector in both Thailand and Poland significantly.

While there has been significant interest in using artificial intelligence (AI) in agriculture, there needs to be more understanding of the factors that drive the adoption of AI-based applications in this sector. While AI has potential benefits in agriculture, such as improved efficiency, yield, and sustainability, there are also significant challenges related to implementing and adopting these technologies. For example, farmers may be hesitant to adopt AI-based applications due to a lack of trust in the technology or concerns about the cost or complexity of implementation. Additionally, there may be cultural and societal factors that influence the adoption of these technologies in different regions or countries. Therefore, the problem that this research aims to address is to compare the contexts of AI adoption in agriculture in Thailand and Poland. Specifically, the research will investigate the technological, economic, and sociocultural factors that influence the adoption of AI in these two countries and the strategies developed to promote their adoption and successful implementation.

By comparing the contexts of AI adoption in these two countries, the research aims to contribute to a better understanding of the factors that drive or hinder the adoption of AI-based applications in agriculture. It sheds light on the strategies that can be used to promote their adoption and success in different contexts. The novelty of this study is that it uses multi-group analysis to investigate the factors that influence the acceptance of AI-based applications in the agricultural sector, emphasizing the poor adoption of AI in agriculture as the problem. The research provided insights on enhancing AI adoption in agriculture, using statistical analysis to identify the factors influencing adoption. The findings from this research can help policymakers, farmers, and investors in the agriculture sector in Thailand, Poland, and other emerging markets by providing statistical evidence for their decisions.

MATERIALS AND METHODS

Understanding the Potential for the Application of AI in Agriculture

AI adoption in agriculture is a growing trend worldwide (*Kernecker et al., 2020; Chaveesuk et al., 2023*), including Thailand and Poland. However, the contexts of AI adoption in these two countries differ due to several factors, including technological infrastructure, economic development, and agricultural practices. Thailand who has a well-established agricultural sector is one of the world's largest rice and other crop producers. However, the country faces several challenges, such as labor shortage, climate change, and water scarcity (*Srivetbodee & Igel, 2021*), which can be addressed by adopting AI technologies in agriculture. For example, AI-based weather forecasting systems can help farmers plan their planting and harvesting schedules and optimize water usage. Moreover, AI-powered drones and robots can be used for crop monitoring, precision agriculture, and weed control, reducing labor costs and increasing productivity.

On the other hand, Poland is a relatively smaller country with a less developed agricultural sector than Thailand (*Kernecker et al., 2020*). However, the government has invested heavily in modernizing its agriculture and developing new technologies to increase productivity and efficiency (*Srivetbodee & Igel, 2021*).

AI technologies can be crucial in modernization by providing advanced data analysis tools, improving decision-making processes, and automating routine tasks. For instance, AI-based soil sensors can help farmers optimize the use of fertilizers, reduce waste, and increase yields (*Chaveesuk et al., 2023*). Although Thailand and Poland have different settings and can both benefit from the use of AI in agriculture, the precise applications of AI will rely on their unique potentials and barriers. However, AI in agriculture can aid both nations in resolving some of the most critical issues affecting their agricultural sectors and boost their competitiveness in the global market.

Technology Adoption Perspective

Embracing technological change is crucial for ensuring business success, and adopting novel technologies or new systems has been widely studied at both the individual and corporate levels. The Theory of Reasoned Action (TRA), as proposed by *Alsheibani et al. (2018)*, sheds light on how beliefs and values shape and direct people's technology adoption behaviors. On the other hand, *Ajzen (2012)* presents the Theory of Planned Behavior (TPB), which emphasizes the impact of an individual's attitude, subjective standards, and perceived behavioral control on their behavioral intentions and actions. Researchers have developed various models and frameworks to understand better what influences users' decisions about when and how to use new technologies. Davis (1986) proposed the Technology Acceptance Model (TAM), which has been validated by numerous studies and highlights the connection between behavioral intentions and actual system usage. However, TAM does not account for qualitative aspects or social forces that shape an Information System (IS) (*Lai, 2017*).

To address this limitation, Venkatesh et al. (2016) developed the Unified Theory of Acceptance and Use of Technology (UTAUT), which explains why people plan on using an IS and how they end up using it. Additionally, the Technology-Organization-Environment (TOE) paradigm, as offered by *Tornatzky et al. (1990)*, characterizes the technical and environmental factors that affect businesses' choices to accept technological innovation. Recent studies, such as those by *Cubric (2020), Mohr and Kühl (2021), Manning et al. (2022), Sood et al. (2022), Rosales et al. (2020), Na et al. (2022), and Kar et al. (2022),* have further investigated the adoption of artificial intelligence (AI) and its impact on various industries, including agriculture, food, construction, and management. These studies emphasize the importance of understanding the drivers, barriers, and social considerations for AI adoption and the critical determinants of adopting AI for sustainable development.

The Contexts of AI Adoption

Over the past few years, there has been a surge in research investigating the effects of AI in various fields. The contexts of AI adoption have been conducted by *Kelly et al. (2023), Ikumoro and Jawad (2019), Sood et al. (2022), Na et al. (2022), Sneesl et al. (2022), Mukherjee et al. (2023), and Al-Dhaen et al. (2021). Phuoc (2022)* states that while a wealth of literature explores AI's theoretical underpinnings and practical applications, there needs to be more research examining how businesses adapt to this rapidly-evolving technology. One notable example of a study that attempts to fill this gap was proposed by *Alsheibani et al. (2018)*, who put forward a framework for studying AI adoption in enterprises. However, their framework is yet to be validated through empirical testing, and little evidence supports their findings. It is challenging to build on conventional constructs and create a thorough comprehension of the factors that impact AI adoption because of the widespread nature of AI and the absence of research on its adoption at the organizational level.

To date, there has been little empirical evaluation of the social acceptability of AI, which is a critical aspect of AI adoption (*Phuoc, 2022*). Thus, further research is needed to explore the factors contributing to the acceptance of AI, including the role of organizational competence and environmental circumstances (Kelly et al., 2023). Previous research has shown that the Theory of Everything (TOE) framework helps examine the factors that facilitate or hinder AI adoption, making it a good starting point for future investigations (*Ikumoro & Jawad, 2019*). The TOE framework comprises three interconnected elements: internal technical factors, internal organizational factors, and external environmental factors (*Na et al., 2022*). To gain a better understanding of the factors that influence AI adoption in a specific industry, researchers may consider incorporating other theoretical models, such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (*Na et al., 2022; Mukherjee et al., 2023*).

Hypotheses and Research Model

According to the literature review, there is a knowledge gap on the enabling factors contributing to firms' AI adoption and how these aspects interact and impact the decision to use AI. In this study, a research approach based on the UTAUT model and Theory of Reasoned Action is proposed to understand better the success factors affecting AI adoption at the organizational level. The UTAUT model includes four fundamental constructs: facilitating conditions, social influence, effort expectancy, and performance expectancy. The organizational context category of success variables includes technology competence, managerial support, organizational size, and AI readiness. This section presents a research model and hypothesis focusing on the Unified Theory of Acceptance and Use of Technology (UTAUT) model and organizational context as the primary determinants of AI adoption in agriculture.

UTAUT Model

The UTAUT model posits that four factors affect technology adoption: performance expectancy, effort expectancy, social influence, and facilitating conditions (*Alkhowaiter, 2022; Sood et al., 2022; Venkatesh et al., 2016*).

Facilitating Conditions

Facilitating Conditions (FC) refer to the availability of resources and support necessary for technology adoption (*Sood et al., 2022*). In AI adoption in agriculture, facilitating conditions include access to reliable internet and digital infrastructure, availability of financial resources, and technical support. The following hypothesis is formulated based on facilitating conditions:

H1: *Facilitating conditions significantly influence the adoption of AI-based applications in the agricultural sector.*

Social Influence

Social Influence (SI) refers to the influence of peers and supervisors on technology adoption (*Fulton et al., 2022; Nascimento & Meirelles, 2021*). In AI adoption in agriculture, social influence could come from peers, industry leaders, government agencies, and research institutions. Industry leaders, such as those in agriculture, can significantly drive adoption through their social influence. The following hypothesis is formulated based on social influence to investigate this influence:

H2: *Social influence significantly influences the adoption of AI-based applications in the agricultural sector.*

Effort Expectancy

Effort Expectancy (EE) refers to the ease of use of the technology (*Jain & Jain, 2022*). In the context of AI adoption in agriculture, effort expectancy could include the complexity of the technology and the ease of integration into existing farm operations. The following hypothesis is formulated based on effort expectancy to examine the claims posited by the researchers:

H3: *Effort expectancy significantly influences the adoption of AI-based applications in the agricultural sector.*

Performance Expectancy

Performance Expectancy (PE) refers to the perceived usefulness of the technology (*Kelly et al., 2023; Sneesl et al., 2022*). In the context of AI adoption in agriculture, performance expectancy could include the potential benefits of the technology, such as increased yields, reduced costs, and improved efficiency. The following hypothesis is formulated based on performance expectancy:

H4: *The adoption of AI-based applications in the agricultural sector is significantly influenced by performance expectancy in the agricultural sector.*

Organizational Context

The organizational context is another critical determinant of technology adoption. In the context of AI adoption in agriculture, the organizational context could include technology competence, managerial support, organizational size, and AI readiness.

Technology Competence

Technology Competence (TC) refers to the organization's technical expertise and experience (*Al-Sharafi et al., 2023; Zhang et al., 2022*). In AI adoption in agriculture, technology competence could include the level of expertise in using digital technologies, familiarity with AI-based applications, and the ability to integrate AI-based applications into existing farm operations. *Manning et al. (2022)* highlighted the importance of ethics in AI adoption in the food sector. The authors argued that a common language for technology adoption across the supply chain was critical for ensuring that AI-based applications were developed and deployed ethically and sustainably. *Manning and colleagues (2022)* emphasized the need for stakeholders to consider the potential ethical implications of AI adoption in the food sector and develop appropriate guidelines and frameworks for ethical technology adoption. The following hypothesis is proposed based on technology competence:

H5: *Technology competence significantly influences the adoption of AI-based applications in the agricultural sector.*

Managerial Support

Managerial Support (MS) refers to the level of support management provides for technology adoption (*Kelly et al., 2023; Sneesl et al., 2022; Balakrishnan et al., 2022*). In the context of AI adoption in agriculture, managerial support could include allocating resources, training, and support for adopting AI-based applications. AI readiness refers to the organization's preparedness for AI adoption, including its ability to handle and manage the technological, infrastructural, and human resource requirements for AI-based applications (*Cubric, 2020*). Several studies have shown that the level of AI readiness can significantly affect an organization's willingness to adopt AI-based applications in agriculture (*Mohr & Kuhl, 2021; Sood et al., 2022*). The following hypothesis is formulated based on managerial support:

H6: *Managerial support significantly influences the adoption of AI-based applications in the agricultural sector.*

Organizational Size

Organizational Size (OS) refers to the organization's size, which could affect its ability to adopt new technologies (*Alsheibani et al., 2018; Na et al., 2022*). In the context of AI adoption in agriculture, smaller organizations may need more resources and expertise to adopt AI-based applications compared to larger organizations. In a study, *Sood et al. (2022)* examined the critical determinants of AI adoption in agriculture. They found that factors such as access to funding, government support, and availability of skilled personnel were critical for enhancing AI readiness. Similarly, *Mohr and Kühl (2021)* investigated the acceptance of AI in German agriculture and identified perceived usefulness, perceived ease of use, and subjective norms as critical determinants of technology adoption. The size of a firm can influence how much it adopts new technologies. Large firms have more resources to invest in research and development (R&D) and training employees on new technologies than smaller firms. Larger firms also tend to be more stable, which means they can afford to take risks with new technologies that smaller firms cannot (*Hradecky et al., 2022*). The authors applied the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) to develop a model for predicting the Intention to Adopt AI (IAA) in the agricultural sector. The following hypothesis is formulated based on organizational size:

H7: *Organizational size significantly influences the adoption of AI-based applications in the agricultural sector.*

H8: *Organizational size significantly mediates the effects of latent variables (Performance expectancy, effort expectancy, social influence, facilitating conditions, technology competence, and managerial support) on adoption of AI-based applications in the agricultural sector.*

Conceptual Framework

The conceptual framework model was developed from the advanced UTAUT model. As seen from the UTAUT model (Fig. 1), the variables used were facilitating condition, social influence, effort expectancy, and performance expectancy. From the organizational context, the variables involved were technological competence, managerial support, and organizational size. The intention to adopt was the dependent variable.

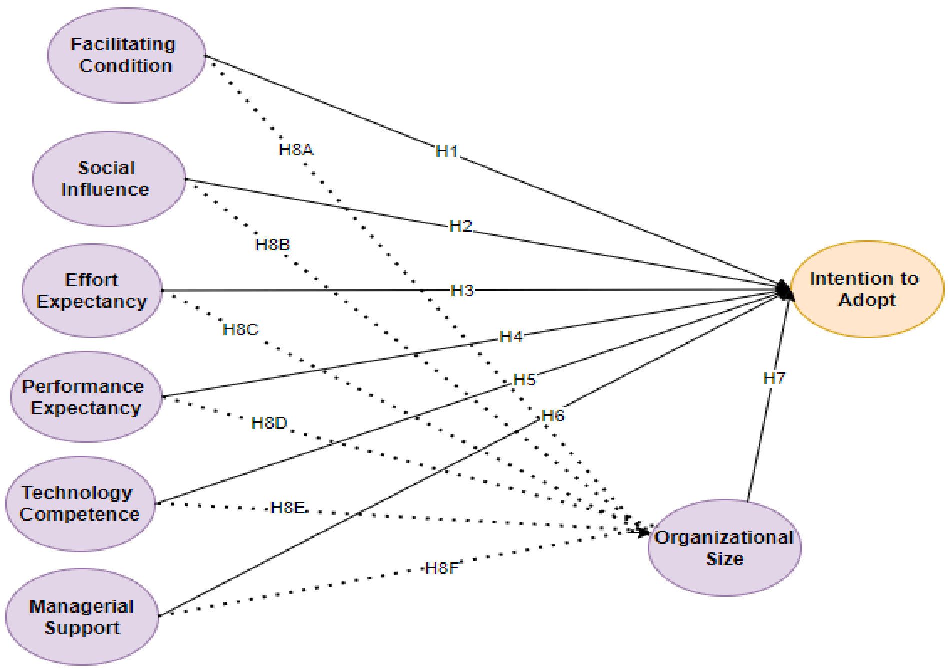

Fig. 1 - Conceptual framework of the study

Methodology

For this study, a quantitative questionnaire was adopted to collect the data. The measurement items used for various latent variables were adopted from the previous studies (Table 1). The 5-point Likert scale was adopted where (1) depicted 'strongly disagree' while (5) depicted 'strongly agree.' Four academicians were consulted to ensure the questionnaire was appropriate, and their feedback regarding the appropriateness was incorporated in redrafting the questionnaire. Since the study was conducted in Thailand and Poland, it was in English and translated into Polish and Thai.

The population of the study was the firms operating in the agricultural sector in Thailand and Poland. The focus was evaluating the factors that determine the adoption of AI-based applications in the sector by firms and other stakeholders operating in the sector. Therefore, the study subjects were individuals in managerial positions, such as human resource managers, operations managers, finance managers, and general managers. These were considered to have appropriate information regarding the adoption and use of artificial intelligence applications in their firms. The targeted sample size was 550 respondents in Thailand and 550 in Poland, totaling 1100 respondents.

A stratified random sampling technique was applied to collect primary data for the study. In both countries, the data was collected from the five central districts of Thailand and five major administrative divisions in Poland. The researchers first contacted the firms and informed on the study's intention. Then the questionnaire was sent using share email addresses to the respondents who answered and emailed back. A total of 1100 copies of the questionnaire were sent out; 550 copies of each questionnaire were sent to respondents in Poland and Thailand, respectively. Of the total sent, 362(65.82%) and 385(70.00%) were received from respondents in Thailand and Poland, respectively. After data cleaning and coding, 356(64.73%) and 377(68.55%) were deemed fit for the analysis.

Structural Equation Modeling (SEM) was applied to conduct the data analysis and to evaluate the hypothesis. However, before the actual analysis, the sample data and model fitness were evaluated for reliability and validity using the measurement model. The Confirmatory Factor Analysis (CFA), construct, convergent, and discriminant validity were analyzed. The measurement model was used to determine the relationship between the latent variables (constructs) and the observed variables (indicators). The structural model was applied to determine the causal relationship between the latent variables (*Chin et al., 2003; Muangmee et al., 2022*). The multi-group analysis evaluated the difference between Thailand and Poland regarding the determinants of AI-based applications adoption in the agricultural sector. The CFA and SEM analysis used the Analysis of Moment Structures (AMOS) software.

RESULTS

Model Evaluation

Reliability, validity, and model fitness tests assessed the measurement model's fitness. The measurement of items and constructs was used to evaluate the model. The convergent validity was estimated by evaluating the study's factor loadings for each of the observed items and the composite reliability (CR) and average variance extracted (AVE) for each construct. The factor loadings whose values were below 0.5 were below the required threshold; hence these items were removed.

Since the analysis involved a multi-group analysis, the adjustment of the CFA was made simultaneously for the two categories. For running the CFA for Thailand and Poland, the factor loadings that were below 0.5 were PE3, PE4, TC4, and TC5. These factors were removed, as they did not meet the threshold. The results after adjustment were as follows. For Thailand, the factor loadings ranged from 0.547 to 0.826, while the AVE ranged from 0.502 to 0.612. These satisfied the required threshold of 0.5 (*Chin and Gopal, 1995; Fornell and Larcker, 1981*). Additionally, the CR values ranged from 0.775 to 0.870, while the values for Cronbach's alpha ranged from 0.786 to 0.873. These values exceeded the recommended threshold of 0.7 (*Chin and Gopal, 1995; Gefen and Straub, 1997*). For the case of Poland, all the observed variable factor loadings satisfied the 0.5 threshold. The factor loadings ranged from 0.589 to 0.842. The AVE ranged from 0.547 to 0.694, which satisfied the required threshold of >5.0. The CR ranged from 0.747 to 0.896, while Cronbach's alpha ranged from 0.752 to 0.899. These values exceeded the minimum threshold of >0.70 (*Chin and Gopal, 1995; Fornell and Larcker, 1981*). As a result, the reliability and validity requirements for the study constructs were achieved.

Table 1

Model evaluation results

	Poland					Thailand				
Latent variables	**Observed Variables**	**Factor loadings**	**CR**	**AVE**	**Cronbach's alpha**	**Observed Variables**	**Factor loadings**	**CR**	**AVE**	**Cronbach's alpha**
EE	EE1	0.761	0.858	0.548	0.861	EE1	0.63	0.817	0.572	0.820
	EE2	0.697				EE2	0.657			
	EE3	0.726				EE3	0.712			
	EE4	0.724				EE4	0.724			
	EE5	0.79				EE5	0.706			
FC	FC1	0.741	0.885	0.607	0.888	FC1	0.717	0.859	0.551	0.862
	FC2	0.746				FC2	0.792			
	FC3	0.821				FC3	0.762			
	FC4	0.811				FC4	0.718			
	FC5	0.774				FC5	0.718			
IAA	IAA1	0.794	0.896	0.633	0.899	IAA1	0.786	0.870	0.573	0.873
	IAA2	0.812				IAA2	0.774			
	IAA3	0.842				IAA3	0.776			
	IAA4	0.739				IAA4	0.683			
	IAA5	0.789				IAA5	0.762			
MS	MS1	0.589	0.828	0.694	0.840	MS1	0.642	0.838	0.509	0.842
	MS2	0.711				MS2	0.733			
	MS3	0.656				MS3	0.756			
	MS4	0.751				MS4	0.734			
	MS5	0.788				MS5	0.698			
OS	OS1	0.759	0.887	0.611	0.888	OS1	0.716	0.848	0.528	0.850
	OS2	0.783				OS2	0.695			
	OS3	0.769				OS3	0.774			
	OS4	0.81				OS4	0.728			
	OS5	0.786				OS5	0.718			
PE	PE1	0.709	0.747	0.596	0.752	PE1	0.68	0.775	0.612	0.786
	PE2	0.752				PE2	0.688			
	PE5	0.649				PE5	0.547			
SI	SI1	0.812	0.867	0.567	0.871	SI1	0.703	0.834	0.502	0.835
	SI2	0.728				SI2	0.724			
	SI3	0.755				SI3	0.686			
	SI4	0.726				SI4	0.733			
	SI5	0.742				SI5	0.694			
TC	TC1	0.684	0.783	0.547	0.791	TC1	0.779	0.823	0.609	0.829
	TC2	0.796				TC2	0.826			
	TC3	0.734				TC3	0.733			

Note: FC = facilitating conditions; SI = social influence; EE = effort expectancy, PE = performance expectancy, TC = technological competence, MS = managerial support, OG = organizational size, IAA = intention to adopt AI.

In addition, the Confirmatory Factor Analysis was conducted to evaluate the measurement model fitness. Various fitness tests in Table 2 are summarized in the figure below. The fit indices are relevant in explaining how the data fit the proposed model. Scholars such as *Byrne (1994), Tucker and Lewis (1973), and Schumacker and Lomax (2010)* recommended that the required threshold for NFI, IFI, and TLI should be 0.9 and above, and GFI should be >0.80. The required threshold for the X2/df threshold is < 5.0, while the threshold for RMSEA is < 0.80 (*Kline, 2015*).

NFI (Normed Fit Index): This is a goodness-of-fit index for SEM models. It indicates how much better the model fits the data in comparison to a baseline model, usually the independence model where all variables are assumed to be uncorrelated. NFI values range between 0 and 1, where values close to 1 suggest a better fit. IFI (Incremental Fit Index): Similar to the NFI, the IFI compares the fits of the target model to an independence model but takes into account model complexity. Like the NFI, IFI values also range from 0 to 1, with values closer to 1 indicating a better fit. TLI (Tucker-Lewis Index): This index also compares the fit of the model to that of an independence model but is adjusted for the degrees of freedom. The TLI is typically less affected by sample size than other indices. Values close to 1 indicate a good fit and values >0.95 are often considered indicative of a good fit. GFI (Goodness of Fit Index): The Goodness-of-Fit Index (GFI) is a measure of how well an estimated model fits the observed data. It varies between 0 and 1, with values closer to 1 indicating a better fit. The GFI considers the relative amount of variances and covariances that the model is able to explain. A commonly accepted threshold for a good fit in the context of GFI is 0.90 or above, although some recommend a more conservative threshold of 0.95. The Root Mean Square Error of Approximation (RMSEA) is a statistic that measures how well a model fits the population's covariance matrix, rather than the sample's covariance matrix. It is sensitive to the number of estimated parameters in the model; thus, it adjusts for model complexity. The RMSEA values range from 0 to infinity, with lower values indicating a better fit. Values of 0.05 or less are considered to indicate a close fit of the model in relation to the degrees of freedom, while values up to 0.08 represent a reasonable error of approximation. $\chi 2/df$ (Chi-Square to Degrees of Freedom Ratio): The Chi-Square to Degrees of Freedom Ratio ($\chi 2/df$) is used to assess the goodness-of-fit of a model. It is calculated by dividing the model's chi-square value ($\chi 2$) by the degrees of freedom (df). A lower $\chi 2/df$ ratio indicates a better fit. Different fields may have different thresholds for an acceptable ratio, but a common rule of thumb is that a $\chi 2/df$ value of 2 or 3 or less signifies an acceptable fit, while some researchers might allow for higher ratios up to 5 in complex models (*Byrne, 1994; Kline, 2015; Schumacker and Lomax, 2010; Tucker and Lewis, 1973*).

For Thailand, the results were X2/df = 2.141, IFI = 0.915, CFI = 0.914, TLI = 0.903, RMSEA = 0.057. These results met the required threshold. For the case of Poland, the results were X2/df = 2.583, IFI = 0.904, CFI = 0.903, TLI = 0.890, RMSEA = 0.065. These results met the required threshold, except for TLI, which was 0.010 less, but satisfied the threshold when rounded off. For both Thailand and Poland cases, these thresholds were satisfied. This confirmed that for both Thailand and Poland, the models used for the study appropriately fit the data.

Table 2

Confirmatory factor analysis

	X2/df	IFI	CFI	TLI	RMSEA
Thailand	2.141	0.915	0.914	0.903	0.057
Poland	2.583	0.904	0.903	0.890	0.065

Empirical results

Case for Thailand

In the case of Thailand, the various factors influencing the adoption of AI in the agricultural sector were evaluated. The results indicated that the facilitating condition has an insignificant and negative influence on the intention to adopt AI (β = -0.077, p = 0.082) hence rejecting H1. Social influence significantly influenced the intention to adopt AI (β = 0.080, p = 0.049), accepting H2. Effort expectancy insignificantly influenced the intention to adopt AI (β = 0.016, p = 0.744) hence rejecting H3. Performance expectancy was found to have a negative and insignificant influence on the intention to adopt AI (β = -0.019, p = 0.684), hence rejecting H4. Technological competence significantly influenced the intention to adopt AI (β = 0.075, p = 0.003), hence accepting H5. Managerial support insignificantly influenced the intention to adopt AI (β = 0.066, p = 0.349), hence rejecting H6. The organizational size was found to significantly influence the intention to adopt AI (β = 0.931, p = 0.000), hence accepting H7. The evaluation of the mediating effect of organization size was also evaluated. The results indicated that organizational size mediated the effect of facilitating condition, effort expectancy, performance expectancy, and managerial support on intention to adopt AI. However, it did not mediate the effect of social influence and technological competence on the intention to adopt AI. The results are summarized in Table 3.

Table 3

Hypothesis results - Case for Thailand

Hypothesis	Relationship			Beta	S.E.	C.R.	P
H1	FC	→	IAA	-.077	.044	-1.741	.082
H2	SI	→	IAA	.080	.041	1.969	.049
H3	EE	→	IAA	.016	.048	.326	.744
H4	PE	→	IAA	-.019	.048	-.401	.689

Hypothesis	Relationship					Beta	S.E.	C.R.	P
H5	TC			→	IAA	.075	.026	2.944	.003
H6	MS			→	IAA	.066	.071	.937	.349
H7	OS			→	IAA	.931	.125	7.454	***
H8a	FC	→	OS	→	IAA	.228	.047	4.812	***
H8b	SI	→	OS	→	IAA	.067	.046	1.451	.147
H8c	EE	→	OS	→	IAA	.113	.056	2.037	.042
H8d	PE	→	OS	→	IAA	.206	.053	3.855	***
H8e	TC	→	OS	→	IAA	-.006	.029	-.195	.845
H8f	MS	→	OS	→	IAA	.575	.071	8.103	***

Note: *** = significant at 99% confidence level; ** = significant at 95% confidence level; FC = facilitating conditions; SI = social influence; EE = effort expectancy, PE = performance expectancy, TC = technological competence, MS = managerial support, OG = organizational size, IAA = intention to adopt AI.

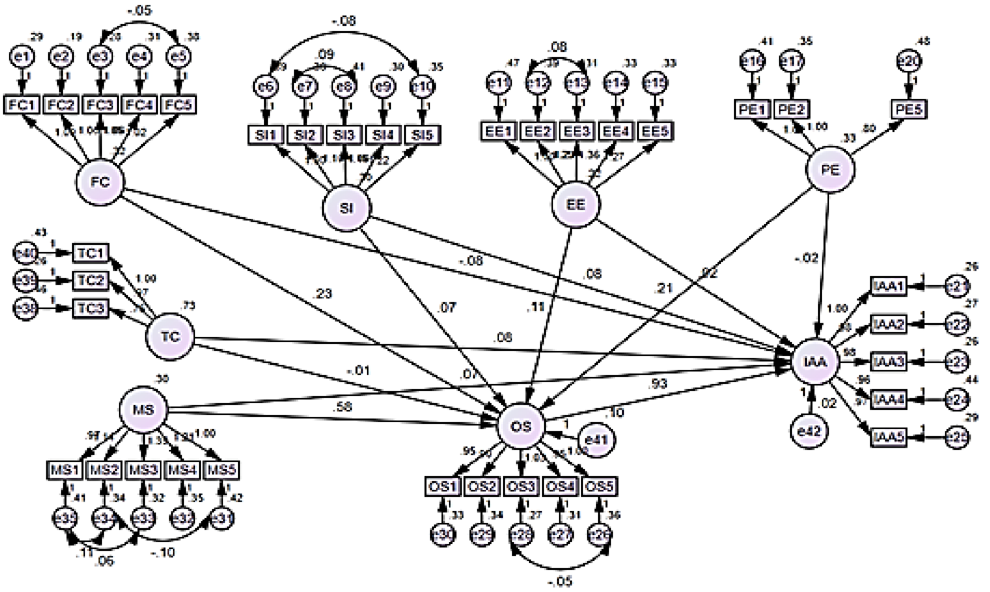

Fig. 2 - Hypothesis results - Case for Thailand

Case for Poland

In the case of Poland, the various factors influencing the adoption of AI in the agricultural sector were evaluated. The results indicated that the facilitating condition positively and significantly influences the intention to adopt AI (β = 0.088, p = 0.014) hence supporting H1. Social influence was found to have a negative and insignificant influence on the intention to adopt AI (β = -0.019, p = 0.637), hence rejecting H2. Effort expectancy was found to have a negative and significant influence on the intention to adopt AI (β = -0.125, p = 0.031) hence accepting H3. Performance expectancy was found to have an insignificant influence on the intention to adopt AI (β = 0.026, p = 0.512), hence rejecting H4. Technological competence significantly influenced the intention to adopt AI (β = 0.136, p = 0.006), hence accepting H5. Managerial support insignificantly influenced the intention to adopt AI (β = 0.080, p = 0.132), hence rejecting H6. The organizational size was found to significantly influence the intention to adopt AI (β = 0.812, p = 0.000), hence accepting H7. In addition, the mediating effect of organizational size revealed that organizational size significantly mediated the effect of all latent variables (social influence, effort expectancy, performance expectancy, technological competence, and managerial support) on the intention to adopt AI, except for facilitating conditions. The results are summarized in Table 4.

Table 4

Hypothesis results - Case for Poland

Hypothesis	Relationships			Beta	S.E.	C.R.	P
H1	FC	→	IAA	.088	.036	2.469	.014
H2	SI	→	IAA	-.019	.039	-.471	.637
H3	EE	→	IAA	-.125	.058	-2.160	.031
H4	PE	→	IAA	.026	.040	.656	.512
H5	TC	→	IAA	.136	.050	2.723	.006
H6	MS	→	IAA	.080	.053	1.507	.132
H7	OS	→	IAA	.812	.108	7.532	***

Hypothesis					Relationships	Beta	S.E.	C.R.	P
H8a	FC	→	OS	→	IAA	.031	.037	.829	.407
H8b	SI	→	OS	→	IAA	-.134	.040	-3.327	***
H8c	EE	→	OS	→	IAA	.424	.053	8.064	***
H8d	PE	→	OS	→	IAA	.152	.041	3.699	***
H8e	TC	→	OS	→	IAA	.234	.049	4.723	***
H8f	MS	→	OS	→	IAA	.409	.045	8.994	***

Note: *** = significant at 99% confidence level; ** = significant at 95% confidence level; FC = facilitating conditions; SI = social influence; EE = effort expectancy, PE = performance expectancy, TC = technological competence, MS = managerial support, OS = organizational size, IAA = intention to adopt AI.

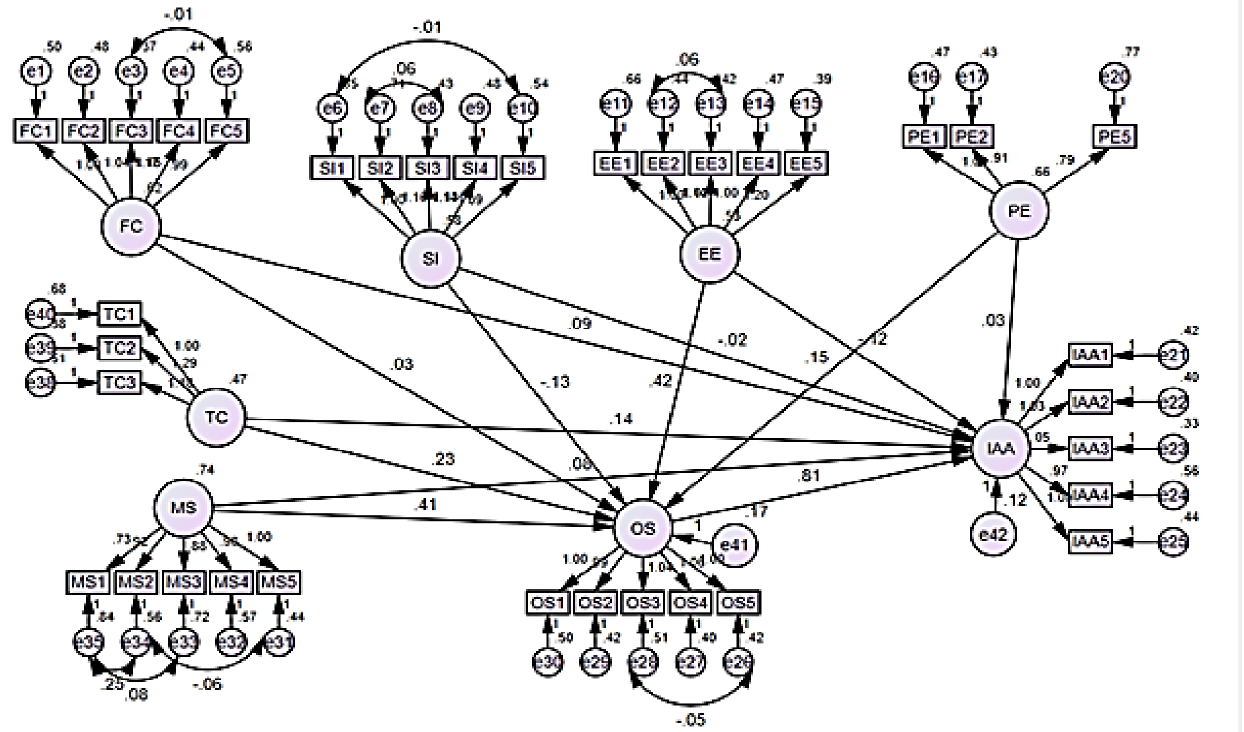

Fig. 3 - Hypothesis results - Case for Poland

Multi-group analysis

The multi-group analysis aimed to evaluate whether the two countries – Thailand and Poland – differed regarding the factors influencing behavioral intention to adopt AI in the agricultural sector. The Chi-square differences for the unconstrained and constrained models were compared. The insignificant paths for Thailand and Poland were deleted to obtain the unconstrained model. To get the constrained model, the paths were named to assume equal paths. The invariance between Thailand and Poland was evaluated by checking the difference between the chi-square and the degree of freedom. The results summarized in Table 5 below show that the Chi-square difference between the two models was 75.69 and that of degrees of freedom difference was 38. The p-value was 0.000 ($p < 0.05$). This implied that the model was not invariant (not indifferent). This meant that the two countries were different, or rather the effect of independent variables on behavioral intention to adopt AI between the two countries was different. These results show that the adoption of AI in the agricultural sector in Thailand was different.

Table 5

Multigroup analysis results

	Chi-square	df	p-val	Invariant?
Overall Model				
Unconstrained	5648.726	1152		
Fully constrained	5724.416	1190		
Number of groups		2		
Difference	75.69	38	0.000	NO

	Chi-square	df	p-val	Invariant?
Chi-square Thresholds				
90% Confidence	5651.43	1153		
Difference	2.71	1	0.100	
95% Confidence	5652.57	1153		
Difference	3.84	1	0.050	
99% Confidence	5655.36	1153		
Difference	6.63	1	0.010	

This research aimed to investigate the determinants of the adoption of AI-based applications in the agricultural sectors of Thailand and Poland, with a comparison of the two countries through a multi-group analysis. The emergence and increasing awareness of the application of artificial intelligence technology in various sectors, including the agricultural sector, drove the research. Different findings were obtained for the case of Thailand and Poland concerning the intention to adopt artificial intelligence in the agricultural sector.

In the case of Thailand, the most influential factor in the adoption of AI applications in agriculture was organizational size. According to the results, an increase of an organizational size by one unit would improve the adoption of AI by 0.931 units for the case of Thailand and 0.812 for the case of Poland. These findings are supported by *Alsheibani et al. (2018) and Kar et al. (2022)*, who indicated that organizational size is a critical aspect because it determines the ability and resources in terms of technology and human resources, which, in turn, significantly influences the ability of the firm to adopt AI technology. The organizational size was a significant mediator between other latent factors and the intention to adopt AI. This indicates that organizational size is a critical factor to consider when determining other aspects that influence the use of AI within the agricultural sector.

The second factor of significance was social influence. The results indicated that if the social influence improves by one unit, the intention to adopt AI applications in agriculture will improve by 0.080 units. Therefore, social influence is necessary to push an organization's AI technological agenda. These findings echo that of *Nascimento and Meirelles (2021),* that the influence of social settings such as peers, industry leaders, government agencies, research institutions, and supervisors of technology adoption is critical towards adopting the technology. Another factor influencing behavioral intention to adopt AI in Thailand was technological competence. These results were supported by *Zhang et al. (2022)*, who indicated that technological expertise within an organization determines how effective its adoption and use of AI technology would be. *Nascimento and Meirelles (2021)* also hold that the social influence from peers, industry leaders, government agencies, and research institutions is critical in determining the future adoption of technology.

Concerning Poland, the results indicated that the factor with the most significant influence is organizational size. The organizational size implies the number of employees, capital level, and levels of operations, among other factors critical for AI technology adoption (*Alsheibani et al., 2012*). More importantly, the organizational size significantly mediated the effect of other factors on their influence on AI adoption in Poland's agricultural sector. The second important factor was technology competence, which implies the knowledge, skills, and capability of taking advantage of the available technology, involving novation and invention. According to the results, one unit's increased technological competence would improve the behavioral intention to adopt AI applications by 0.136 units. Other factors that significantly influenced the adoption of AI in Poland's agricultural sector were facilitating conditions and effort expectancy. These results were in line with that of *Sood et al. (2022),* that the availability of resources, internet access, digital infrastructure, and financial resources are the necessary facilitating conditions that enhance technology adoption in the concerned setting or organization.

An extended analysis revealed that when comparing Thailand and Poland, the results indicated a significant variance in the determinants of adopting AI applications in the agricultural sector. For Thailand, the relevant factors include organizational size, managerial support, technological competence, effort expectancy, and social influence. For Poland, the relevant factors include organizational size, managerial support, technological competence, and facilitating conditions.

From the study, both the managerial and theoretical implications were developed. Regarding the theoretical implications, this research developed a conceptual model by borrowing from two broad perspectives – the UTAUT model and the organizational context. From the UTAUT model, the variables used were facilitating conditions, social influence, effort expectancy, behavioral intention to adopt, and performance expectancy. From the managerial perspective, the following aspects were used - technological competence, managerial support, and organizational size. The model established the relationship between the study variables. The study added to the literature by evaluating the factors influencing the intention to adopt AI applications in the agricultural sector in Thailand and Poland by performing a multi-group analysis. From the empirical perspective, this research evaluated the factors influencing the intention to adopt AI applications in the agricultural sector. The research contributes to the literature through the findings that in Thailand, the intention to adopt AI-application in the agricultural sector is influenced by organizational size, technological competence, and social influence, while in Poland, the intention to adopt AI applications in the agricultural sector is influenced by organizational size, technological competence, effort expectancy, and facilitating conditions. Another critical implication is that regarding the adoption of AI applications in Thailand and Poland, the influencing factors are variants.

Several recommendations were developed concerning the application of AI in the agricultural sector. First, this research found that organizational size is the most influential factor in adopting AI applications in the agricultural sectors. Therefore, improving the organizational size in terms of resources, capabilities, and structures would enhance the ability to adopt AI technology. For Thailand, the other factors that should be enhanced include technological competence and social influence within an agricultural firm, which go a long way toward promoting AI adoption. For Poland, the other factors that the policymakers should improve include effort expectancy and technological competence. In addition, the facilitating condition is vital in Poland.

CONCLUSIONS

This research aimed to investigate the determinants of AI-based application adoption in the agricultural sectors in Thailand and Poland. This research was driven by the recent increased development of artificial intelligence and its application in various sectors to improve business processes and performance. AI has been considered to transform the agricultural sector through improved efficiency and productivity significantly. Two theories guided this research – the Theory for Reasoned Action (TRA), the Theory of Planned Behavior (TPB), and the Unified Theory of Acceptance and Use of Technology (UTAUT). The study used primary data collected from people working in the agricultural sectors in Thailand and Poland. From a sample target of 1100 respondents, 356 and 377 respondents in Thailand and Poland were used, respectively. The confirmatory factor analysis (CFA) was used to evaluate the model's fitness, reliability, and validity. The hypotheses were tested using Structural Equation Modeling (SEM).

The results revealed that for Thailand, the determinants for AI-based application adoption were organizational size, managerial support, technological competence, effort expectancy, and social influence. In Poland, the determinants for AI-based application adoption were organizational size, managerial support, technological competence, and facilitating conditions. The multi-group analysis revealed that the two countries were not invariant; hence the effect of independent variables on behavioral intention to adopt AI between the two countries was different. The research recommended that Thailand and Poland's agricultural sectors differ, therefore, specific factors should be considered in AI-based application adoption.

In conclusion, the adoption of AI-based applications in the agricultural sector is influenced by various determinants, including factors related to farmers' characteristics and organizational, technological, and external factors. The findings of this study highlight the importance of understanding these determinants and their respective impacts on the adoption process. By addressing the identified determinants, stakeholders in the agricultural sector can develop effective strategies to facilitate the adoption of AI-based applications and achieve their full potential in improving agricultural productivity and sustainability. However, it is important to note that adopting AI-based applications is a complex process that requires careful planning, investment, and collaboration among various stakeholders. Further research is needed to investigate the impact of these determinants in different contexts and to identify additional factors that may affect the adoption of AI-based applications in the agricultural sector.

ACKNOWLEDGEMENT

The research was carried out with financial aid and assistance from KMITL Business School, King Mongkut's Institute of Technology Ladkrabang under grant number 2565-02-12-006. The authors also acknowledge the reviewers' support, whose feedback and criticisms helped draft the published version.

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