Barriers to Industry 4.0 technology adoption in agricultural supply chains: A Fuzzy Delphi-ISM approach

Abstract

Purpose - The purpose of this study is to identify and analyze the barriers associated with the adoption of Industry 4.0 technologies in agricultural supply chains.

Design/methodology/approach - The study initially identified thirteen barriers by conducting a literature review and semi-structured interviews with key stakeholders. Subsequently, these barriers were validated and modeled using an integrated Fuzzy Delphi-ISM approach. Finally, MICMAC analysis was employed to categorize the barriers into distinct clusters.

Finding - The results provide considerable insights into the hierarchical structure and complex interrelationships between the barriers as well the driving and dependence power of barriers. Lack of information about technologies and lack of compatibility with traditional methods emerged as the two main barriers which directly and indirectly influence the other ones.

Research Implications – The robust hybrid Fuzzy Delphi and ISM techniques used in this study can serve as a useful model and benchmark for similar studies probing the barriers to Industry 4.0 adoption.

Practical Implications: The study is timely for the post-COVID-19 recovery and growth of the agricultural sector. The findings are helpful for policymakers and agriculture supply chain stakeholders in devising new strategies and policy interventions to prioritize and address Industry 4.0 adoption barriers.

Originality/Value: It is the first comprehensive, multi-country and multi-method empirical study to comprehensively identify and model barriers to Industry 4.0 adoption in agricultural supply chains in emerging economies.

Keywords: Industry 4.0, Barriers, Agriculture, emerging countries, Interpretive Structural Modeling (ISM), Fuzzy Delphi technique

1. Introduction

Agriculture is critical to socio-economic development. However, it is increasingly faced with the challenges of ensuring security, safety and sustainability (of food): around 800 million people suffer from hunger/malnutrition and 9 million die of starvation each year (De Clercq et al., 2018; World Food Programme, 2021), while conventional farming methods, unpredictable weather, pests, diseases and soil quality issues depress productivity and crop yield (Rahman et al., 2018; Singh and Agrawal, 2021; Masud et al., 2017). Other challenges include leakages with around 15% of the produce lost in transport and storage (Kumar et al., 2021), and 40% of the food not eaten and wasted (World Food Programme USA, 2021). There are further environmental and safety issues: food accounts for around 8% of the global greenhouse gas emissions (Chartered Institute of Environmental Health, 2021; The Washington Post, 2018) and involves consumption of roughly 25% of the global freshwater (UNECE, 2021); it is also associated with frequent (foodborne) illnesses and contamination such as salmonella outbreak and mad cow disease. These challenges are only going to intensify in the future as the food requirement increases (due to the growing population), and agriculture land availability reduces (from the growing urbanization) (United Nations, 2017; van Dijk et al., 2021). Potential solution/s could be through the use of advanced technologies (World Bank, 2019; Yadav et al., 2022, Psomas and Deliou ,2023).

Industry 4.0 technologies such as Internet of Things (IoT), Radio Frequency Identification (RFID), Wireless Sensor-based Networks (WSNs), Big Data Analytics, Artificial Intelligence (AI), Blockchain, Cloud Computing, Autonomous Vehicles/Machineries, and Robotics have gained popularity across many sectors (Yadav et al., 2020; Balasubramanian et al., 2021a; Stocco et al., 2022). In agriculture's case, they could make the supply chains more intelligent, integrated, data-driven, agile, and autonomous and thereby improve their operational efficiency, responsiveness and traceability (Soosay and Kannusamy, 2018). Industry 4.0 also contributes to the development of sustainable supply chains, and circular economy models (Stocco et al., 2022). However, their diffusion/adoption rate in the agricultural sector continues to be low, which is a cause for concern, but which also reflects the barriers faced in (their) implementation (Soosay and Kannusamy, 2018; Akella et al., 2023). Understanding these barriers including their nature, characteristics, and interrelationships is therefore important; it would enable suitable policy actions to be designed to counter them. This forms the focus of the present work where there have only been a few previous studies, i.e., those focused on barriers to Industry 4.0 implementation in agriculture. They have also been predominantly exploratory/descriptive (e.g., Long et al., 2016), or specific; for example, barriers to specific technologies such as Blockchain (Yadav et al., 2020; Akella et al., 2023) or IoT (Narwane et al., 2022) in agriculture. The lone somewhat comprehensive study by Kumar et al. (2021) also focused on only one country (India), and only on Industry 4.0 barriers from the perspective of circular economy in agriculture. This comprehensive, multi-country study with a holistic Industry 4.0 technology orientation therefore aims to:

1) Identify the barriers to Industry 4.0 technology adoption in agricultural supply chains
2) Model these barriers based on their hierarchical structure and interrelationships
3) Cluster and prioritize these barriers based on their characteristics (driving and dependence power)

The barriers (that are identified) highlight all the key challenges that need to be addressed to intensify the adoption of Industry 4.0 technologies in agriculture. Further modeling these barriers helps in comprehending the causal interrelationships between them. Finally, clustering them based on their driving and dependence power enables the development of suitable policy prescriptions and counter-measures to address the critical ones.

With agriculture being particularly important to emerging countries, we selected an important region from there, specifically, the Greater Mekong Subregion (GMS) for this study. It is a transnational region that includes Cambodia, Laos, Myanmar, Thailand, Vietnam and two provinces of China. Agriculture is the backbone of this region's economy (Chanchaichujit et al., 2017); also, conventional agriculture practices are dominant there, and where therefore, advanced technology (particularly Industry 4.0 related) could make a significant contribution (GMS, 2021).

The contributions of the study are manifold. It is the first comprehensive, multi-country and multi-method empirical study that models Industry 4.0 adoption barriers in agriculture. The structural model for barriers that is proposed is not seen in previous studies, and therefore constitutes a novelty, as do the findings on the barriers themselves. Also, while the focus is on GMS countries, the fact that agriculture issues are similar in other emerging ones means that the learnings can be applied there. Secondly, it offers practical insights to agriculture policymakers and stakeholders so that they can develop suitable strategies and policy interventions to diminish the impacts of the barriers. The resulting greater implementation of advanced technologies will allow the sector to recover faster from the recent COVID-induced economic devastation. Finally, from a methodological standpoint, the sequential Fuzzy Delphi-ISM approach (that is used) contributes to the literature on multi-criteria decision frameworks (Bianco et al., 2021).

The rest of the paper is structured as follows. The next section outlines Industry 4.0's potential for agricultural supply chains. Section 3 details the multistage research framework and the different research methods used. The study findings are presented in Section 4 and then discussed in Section 5. We conclude in Section 6 where the study's implications, limitations, and suggestions for future work are covered.

2. Industry 4.0 Application in Agricultural Supply Chains

Agricultural supply chains are complex and fragmented and consist of a multitude of stakeholders including input suppliers (fertilizers, pesticides, equipment, machinery, etc.), farmers, food producers, food processors, logistics service providers, technology solution providers, and consumers that are associated with the different stages of the supply chain, namely, pre-cultivation, cultivation & harvesting, and processing & distribution (Yadav et al., 2022). Various Industry 4.0 technologies can be applied at these stages including generic ones such as big data analytics, artificial intelligence, blockchain, and cloud computing, and specific ones such as gene-editing (of crops) in pre-cultivation, drones for seed planting, autonomous robots for harvesting, and autonomous forklifts and smart containers for processing and distribution. Please refer to figure 1 for the details.

The key activities in pre-cultivation include selecting appropriate arable land, crops, and sowing period/s. The role of technology is critical here given the unpredictability of the weather/climatic conditions and the soil quality (Masud et al., 2017; Singh and Agrawal, 2021). Data such as on historical weather patterns and on others from satellite (images), drone (images) and GPS systems are therefore used with artificial intelligence techniques (machine learning and deep learning) to inform on soil quality, seeds, disease probability, crop yield and fertilizer selection (De Clercq et al., 2018). A specific case is the use of surveillance drones with computer vision to make precise 3D maps for early soil analysis, and to gather data for managing irrigation and on nitrogen levels (De Clercq et al., 2018). Further, gene editing of crops or genetic modification (e.g., drought-resistant wheat) is used to improve yield (Long et al., 2016; De Clercq et al., 2018).

In the cultivation and harvesting phase, advanced technologies are used to optimize resource usage and to reduce waste. Multisource data is typically used with these technologies that enable precise monitoring and decision-making on agricultural processes, and which is also referred to as precision agriculture (Smania et al., 2022). For example, with regards to farm inputs, data on soil and field conditions captured through a Wireless Sensor-based Network (WSN) is analysed to make precise and specific interventions on irrigation, fertilizers, nutrients, and pesticides (Ayamga et al., 2021). Similarly, autonomous drones with computer vision (camera and sensors) (Gonzalez-de-Santos et al., 2017) are used to assess crop growth/development and to alert farmers to any diseases, weeds, or abnormalities (De Clercq et al., 2018; Ayamga et al., 2021). Also, precision drone planting systems can shoot pods with seeds and nutrients into the soil, and also provide necessary nutrients to grow them, thereby reducing planting costs by up to 85% while also increasing yield (De Clercq et al., 2018). They can also plant seeds in remote locations thereby lowering equipment and workforce costs; also, survey crops and herds over vast areas quickly and efficiently. Similarly, crop pesticide spraying through drones is five times faster than conventional spraying, and with lesser material wastage (De Clercq et al., 2018). Further, autonomous/self-driving equipment could help address driver/labour shortages and enable large agricultural holdings to be effectively and efficiently managed (Nokia, 2022; World Economic Forum, 2022). Finally, robots could be used for picking apples and strawberries, harvesting lettuce, and stripping away weeds (Builtin, 2022). With computer vision, artificial intelligence and robotic arms, they can do these tasks more efficiently and accurately than human beings.

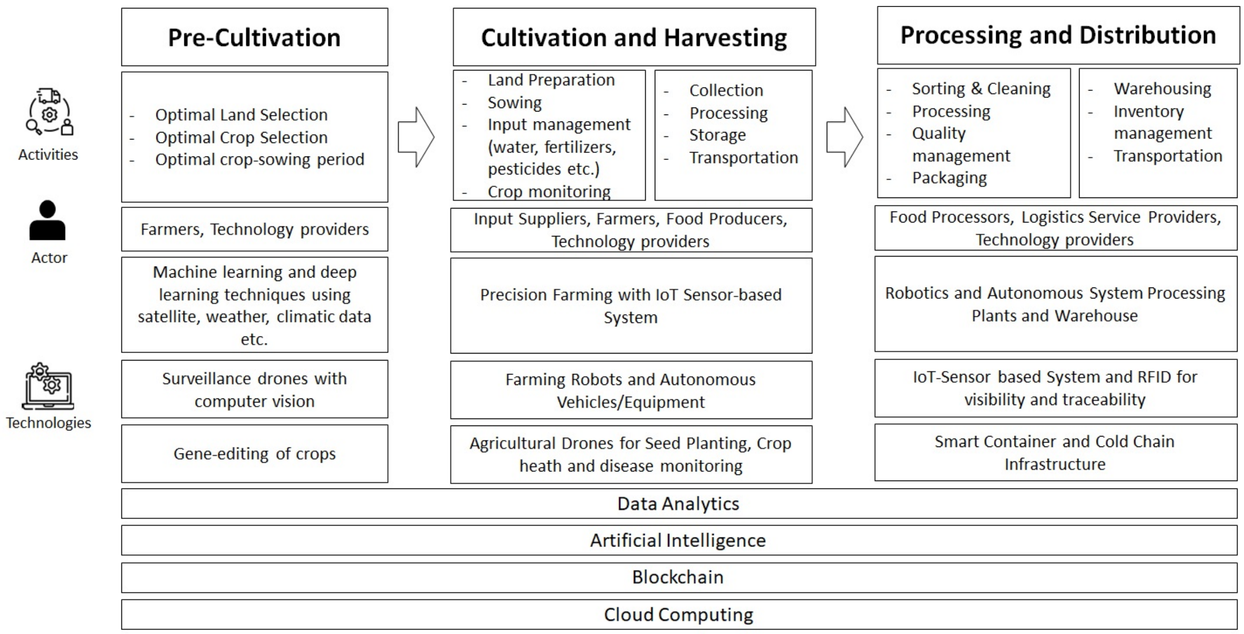

Figure 1. Industry 4.0 Application in Agricultural Supply Chain (Source: Authors)

Digitization/automation has also been exploited in the processing and distribution phase with a key area being waste reduction (Yadav et al., 2022). For example, for transporting fresh produce, smart containers with sensors, GPS tracking and Internet of Things (IoT) technologies are used, that provide real-time tracking, and can alert operators to any quality or theft-related issues (Global Infrastructure Hub, 2022); they can also automatically regulate the internal operating conditions (e.g., temperature, humidity), if required. A similar RFID-based food traceability system can ensure food safety. Further, the data associated with these technologies can be made tamper-proof/fraud-resistant by transferring it to a Blockchain (Alkhoori et al., 2021). Other technologies include autonomous or robotic (driverless) forklifts, which can operate with nearly 100% accuracy, and with fewer accidents/injuries during loading/unloading (Hyster, 2022). Their use not only increases productivity, but also lowers costs with less product damage and no employee leave/absenteeism-related problems. Similarly, an autonomous mobile robotic base (AMRB) can perform repetitive, nonvalue-added tasks of moving material autonomously to desired location/s, and it can do so safely as it reacts, i.e., stops or drive around people, trucks or other obstacles (Mecalux, 2021).

For the end-to-end supply chain, Blockchain technology can be used (Wang et al., 2019). It enables anonymity and integrity, with any IoT/sensor/other data fed to it becoming immutable, and subsequent changes easily and transparently traceable. This promotes increased data sharing among supply chain stakeholders, with the consequent high provenance enhancing food safety and quality (Yadav et al., 2022), and eliminating green washing. The (consequent) large amount of shared data can be exploited to improve the tracking/tracing (of goods and documents), as also the planning and optimization of resources and facilities across the supply chain. The potential for such big data-oriented applications in agricultural supply chains is enormous (Yadav et al., 2022). Further, smart contracts operating on blockchains can prevent price extortion and payment delays, while also reducing transaction fees (because of elimination of intermediaries). For farmers, this would mean fairer pricing and a greater share of their crop's revenue (De Clercq et al., 2018, Yadav et al., 2022). Finally, cloud computing enables computing services like storage, servers, networking, analytics, intelligence and software to be delivered over the internet in a pay-as-you-go mode (Yadav et al., 2022). This makes them more affordable (and therefore implementable) for small-scale farmers, who lack the financial muscle to make their own large investments in IT infrastructure.

3. Research methodology

The research methodology flows from the research objectives. The research framework adopted in this study is shown in Figure 2.

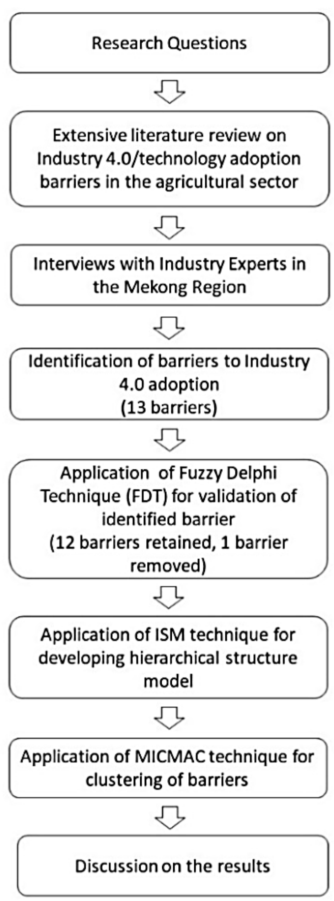

Figure 2. Research Framework

3.1. Research Setting

The research setting needs to be appropriate to the research objectives. We carefully selected the Greater Mekong Subregion (GMS) for this study because agriculture is critical to the socio-economic development there: 60% of its 340 million inhabitants are engaged in agriculture activities (GMS, 2021). However, agriculture's share of Gross Domestic Product (GDP) in the region has fallen sharply; for example, agriculture sector's contribution to GDP in Cambodia has declined from around 35% in 2011 to around 23% in 2021 (Statista, 2022a). This is largely due to a reduction in the sector's productivity, quality, and profitability. Most governments in the region have recognized this adverse trend and have urgently focused efforts on reversing it through the use of Industry 4.0 technologies (World Economic Forum, 2022). For instance, in Thailand's case, several measures have been undertaken to move towards smart farming i.e., through use of technologies such as remote sensing, geo-mapping, and drones (Statista, 2022b). Similarly, in Cambodia, RFID and blockchain technologies have been piloted to improve food traceability, while AI, sensors and drones have been tried for enhancing the overall farming productivity (UNDP, 2021). The GMS region therefore serves as a relevant and interesting context for conducting the investigation.

An extensive but pragmatic literature review was conducted to address the first objective, which is to identify the barriers to Industry 4.0 adoption in agricultural supply chains. The pragmatic approach is justified given that practical/realistic insights are needed to inform practice, especially considering the novelty of the topic (Balasubramanian et al., 2021b). It involved searching for specific studies (barriers + Industry 4.0 + agriculture), and on finding only a few, extending the search to barriers to adoption of other advanced technologies in agriculture, and barriers to Industry 4.0's adoption in other sectors. In addition, we also reviewed relevant reports from GMS governments, global organizations such as World Bank, World Economic Forum, United Nations, OECD, Asian Development Bank, and leading consulting firms. The information gathered from the review was assembled, coded, and analyzed to generate a comprehensive list of barriers to Industry 4.0's adoption in agriculture; also, the barriers could be categorized into four distinct groups, namely, i) Economic barriers; ii) Institutional/regulatory barriers; iii) Behavioral/psychological barriers; and iv) Organizational barriers (Long et al., 2016).

3.2. Semi-structured Interviews

In the next stage, interviews with 21 industry experts from the GMS region (refer Appendix A) were conducted to shortlist the key Industry 4.0 barriers for agriculture in the region. Here, a purposive sampling technique was employed to encompass various stakeholders in the agricultural sector, ensuring adequate representation from both technology adopters, such as food processors and transport/logistics companies, and technology providers, including drone manufacturers and automation solution providers. This sampling approach also guaranteed the capture of diverse perspectives from the public sector, private sector, and industry associations. Further, purposive sampling ensured there is representation from different countries in the GMS.

A semi-structured interview protocol was adopted, preferred due to the scope of the interviews, which covered four categories of barriers: economic, institutional/regulatory, behavioral/psychological, and organizational. The interviews, conducted via Zoom, typically lasted between 30 and 45 minutes. Barriers identified from the interviews within each category were subsequently coded. For instance, 'high cost of implementation,' a key barrier identified during interviews, was coded and categorized under economic barriers (ECB1)." The semi-structured nature of the interviews facilitated easy comparison of responses against the alternative unstructured interview approach, which is susceptible to information overload (Balasubramanian et al., 2017). This method helped in narrowing down the list of barriers from over 30, identified from the literature, to 24, retaining only those that were highlighted both in the interviews and the literature review and excluding those found only in the literature. Subsequently, the 'mutually exclusive and collectively exhaustive' principle was applied to ensure there was no repetition or overlap between the barriers. For instance, barriers like lack of financial support from the government, absence of subsidies, incentives, and tax concessions were analogous and were thus consolidated under a single barrier termed 'low government support.' Similarly, barriers such as high upfront cost of implementation, operational costs, and hidden costs were unified under 'high cost of implementation,' further reducing the number of barriers to 13.

3.3. Fuzzy Delphi Technique (FDT)

In the next phase, the Fuzzy Delphi Technique (FDT) was used to validate and finalize the barriers. The use of FDT vis-à-vis traditional qualitative methods such as in-depth interviews and Delphi methods to gather insights from experts was Ratbecause such methods can be time-consuming and are often prone to yielding vague/uncertain exploratory results (Phellas et al., 2011; Rathore et al., 2022). Conversely, the advantage of Fuzzy Delphi Method (FDM) mitigates the uncertainty and imprecision inherent in experts' assessments (Gupta et al., 2022), addressing scenarios where humans cannot draw precise conclusions (Rathore, 2021; Rathore and Gupta, 2021). FDT is based on the theory of fuzzy sets (Singh and Sarkar, 2020) and involves collecting experts' ratings on each of the factors on a fuzzy linguistic scale. This approach thereby offers a more structured and precise alternative for capturing expert opinions and insights. These factor ratings are then compared with a computed threshold value to decide which to retain/exclude. In this study, 23 industry and academic experts were consulted (refer Appendix B) who rated the importance of each barrier (13 in total) on a fuzzy linguistic scale. The sample of 23 experts is well above the recommended one of 15 (Rathore et al., 2022); also, purposive sampling was used for their selection so as to ensure representation from all the GMS countries and stakeholders.

The following steps were followed (Rathore et al., 2022):

Step 1 - Prepare a questionnaire with all the barriers and ask experts (n) to rate the importance of barriers (m) on a fuzzy linguistic scale, as shown in Table 1. The use of fuzzy linguistic scale is because decision-makers often find assigning linguistic variables to judgments more intuitive and straightforward than making fixed value judgments (Chen et al., 2011). The scale allow for a high level of expressiveness, enabling individuals to articulate their preferences, feelings, or judgments in natural language terms rather than in rigid numerical terms. Linguistic terms are user-friendly and more intuitive to individuals, thus effectively addressing uncertainty and imprecision and allowing for a more nuanced and accurate representation of real-world problems (Chen et al., 2011). Next, the relationship between linguistic variables and fuzzy sets was used to transform the evaluation of qualitative indicators by experts into quantitative fuzzy numbers (Li et al., 2022).

Table 1. Fuzzy Linguistic Scale for FDT

Linguistic Terms	Codes	Corresponding TFN
No Influence	NI	(0.1, 0.1, 0.3)
Low Influence	LI	(0.1, 0.3, 0.5)
Medium Influence	MI	(0.3, 0.5, 0.7)
High Influence	HI	(0.5, 0.7, 0.9)
Very High Influence	VI	(0.7, 0.9, 0.9)

Step 2 - Inputs of experts for each barrier is converted into triangular fuzzy numbers (TFNs) denoted as (p, q, r). A fuzzy number corresponding to the j^{th} barrier provided by i^{th} expert is represented as:

$Z_{ij} = (p_{ij}, q_{ij}, r_{ij})$ for $i = 1, 2, 3, \dots n$ and $j = 1, 2, 3, \dots m$, where n represents the number of experts and m represents the number of barriers.

Step 3 - Calculate the fuzzy weights of barriers as follows:

$$p_j = \min[p_{ij}]\,; r_j = \max[r_{ij}]\,;$$

$$q_j = \left(\prod_{i=1}^{n} (q_{ij})\right)^{1/n}$$

Step 4 - Apply the centre of gravity method to calculate the defuzzification value S_j as given below:

$$S_j = \frac{(p_j + q_j + r_j)}{3}, j = 1, 2, 3, \dots m$$

Step 5 - Compare the weights of all barriers against the threshold value (α), which is considered a benchmark for accepting or rejecting a barrier. The α is obtained by taking the arithmetic mean of the defuzzification values for all 13 barriers. If $S_j \geq \alpha$, then the barrier is retained; if $S_j < \alpha$; then the barrier is removed. As per this analysis, 12 of the 13 barriers were retained with one excluded.

3.4. Interpretive Structural Modelling (ISM)

In line with our second research objective, Interpretive Structural Modelling (ISM) was applied to the barriers to generate an associated hierarchical structure with interrelationships (Karadayi-Usta et al, 2020). ISM involves the use of expert knowledge and experience to convert complex socio-economic systems into more lucid forms to improve understanding (Warfield, 1974). The outcome of ISM is an interconnection framework where a set of directly and indirectly related elements are mapped into a contextual model (Gadekar et al., 2022).

While prior literature highlights the availability of other multi-criteria decision-making (MCDM) methods, such as the Decision-Making Trial and Evaluation Laboratory (DEMATEL) and Analytical Hierarchical Process (AHP) to discern interrelations amongst barriers, this study has employed ISM since it holds a distinctive advantage over other MCDM methods as it adeptly transforms vague models into hierarchically structured and well-articulated barriers (Rathore et al., 2022). Some of the key advantages of ISM over other MCDM techniques are as follows (Sushil, 2012; Rathore et al., 2022; Sorooshian et al., 2023):

- ISM excels in managing and representing complex, interrelated, and interdependent systems and relationships within a structured and visual model, especially in sociotechnical and organizational contexts, making it easier to understand the relationships among different components or variables. However, other MCDMs such as AHP require precise quantification and prioritization of decision criteria.
- ISM is more user-friendly because its binary scale and algorithm are designed to avoid inconsistencies. However, others such as DEMATEL require a larger range of scales to complete the cause-and-effect interactions.
- ISM offers robust visualization of relationships and hierarchies among elements or variables, allowing decision-makers to gain insights into the systemic interconnections and dependencies, which can be crucial for understanding complex and multifaceted problems and systems.
- ISM is particularly advantageous for conducting qualitative analysis. It helps structure and interpret subjective judgments and qualitative information. In contrast, AHP largely relies on quantitative data and requires exact numerical input.
- ISM can be used with the cross-impact matrix multiplication applied to classification (MICMAC) for identifying driving and dependent factors in a system, allowing for a deeper understanding of the influences and dependencies among various barriers.

ISM has previously been used to examine barriers, and in various contexts (Karadayi-Usta et al., 2020; Kamble et al., 2023). For example, Rathore et al. (2022) used ISM to examine the interrelationships between barriers to adoption of disruptive technologies in the logistics sector. Similarly, Balasubramanian (2012) utilized ISM to model the barriers affecting green supply chain management practices' implementation in the construction sector. With regards to studies involving agriculture, while Kumar et al. (2021) used ISM to analyse Industry 4.0 and circular economy adoption barriers in the sector, barriers to blockchain technology adoption were studied via ISM by Yadav et al (2020).

The flow chart representing ISM steps is given in Figure 3. The details on the execution of each step are given below (Ghobakhloo, 2020; James et al., 2023):

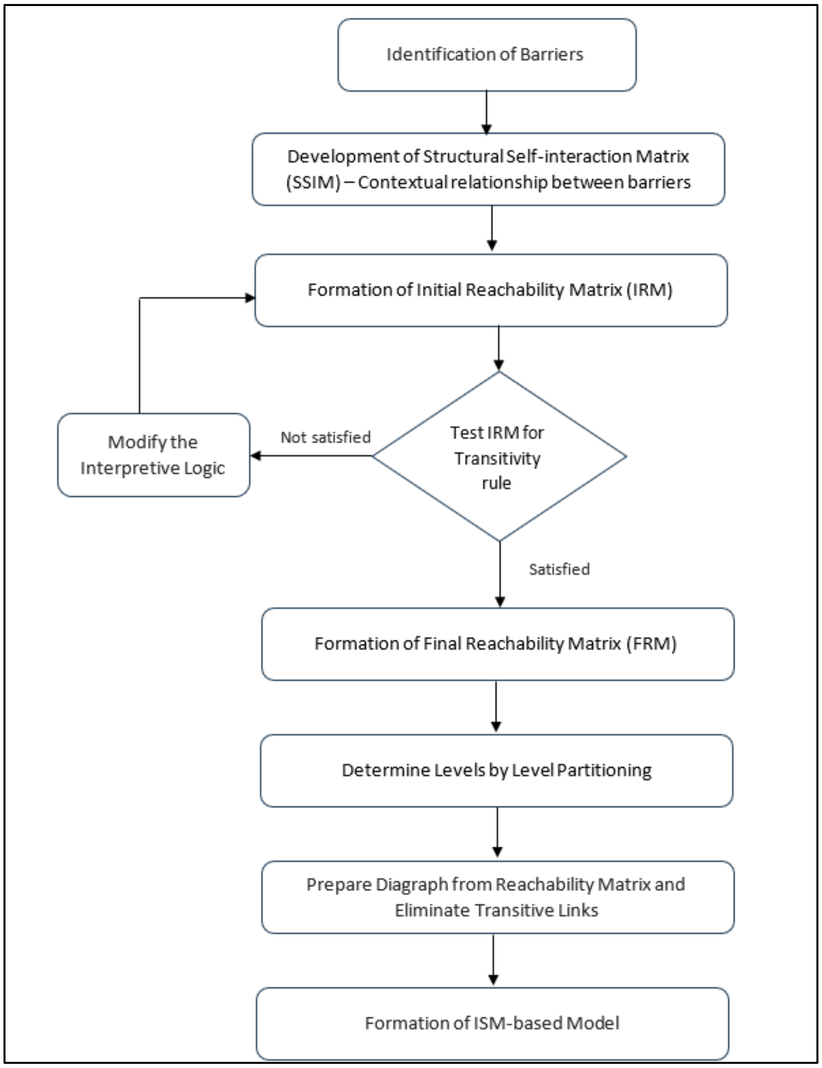

Figure 3. ISM Methodology (Adapted from Sushil (2012) and Cherrafi et al. (2017))

Step 1 – Identify barriers to the adoption of Industry 4.0 technologies in the agricultural supply chain (output from FDT was used)

Step 2 – Develop the structural self-interaction matrix (SSIM) based on inputs from domain experts who indicate the relationships between the barriers using the symbols V, A, X, O. Here the same 23 domain experts used for FDT were used. The meaning of these symbols is as follows:

V: Barrier i i will influence barrier j;

A: Barrier j will influence barrier i;

X: Barrier i and j will influence each other and

O: Barriers i and j are unrelated

The individual SSIM matrices for each expert (and 23 in total) were then combined into a unified SSIM as per the suggestions of Muruganantham et al. (2018). This meant using the mode of different experts' responses on a matrix entry as the corresponding unified matrix entry.

Step 3 – Develop the initial reachability matrix (IRM). It is developed by converting the SSIM matrix into a binary one, where V, A, X and O are substituted by binary numbers 1 and 0 as per the substitution rules shown in Table 2. In addition, the main diagonal elements are assigned a 1, since i and j are equal.

Table 2. Replacement of contextual relationship by binary numbers

SSIM Value	**Binary replacement**	
(i,j)**entry**	(i,j) **entry**	(j,i)**entry**
V	1	0
A	0	1
X	1	1
O	0	0

Step 4 – Develop the final reachability matrix (FRM). It is obtained after incorporation of transitivity in the IRM to identify the indirect relationships between the barriers. The transitivity of the contextual relation is a basic assumption made in the ISM. It states that if X is related to Y and Y is related to Z, then X is essentially related to Z.

Step 5 - Partitioning of the final reachability matrix (FRM) (establishing the hierarchy level of barriers). The hierarchy level for Industry 4.0 barriers in this study is developed using the reachability, antecedent, and intersection sets for each barrier based on the values from the FRM.

The reachability set expressed as $R(B_i)$ consisted of the barrier (B_i) itself and other barriers affected by it.

$$R(B_i) = \{x \mid (i,x) = 1\}$$

The antecedent set expressed as $A(B_i)$ comprised of the barrier itself (B_i) and other barriers that may have affected it.

$$A(B_i) = \{x \mid (x,i) = 1\}$$

The intersection set, expressed as $I(B_i)$ for each barrier (B_i) consists of the intersection among the pair of reachability and the antecedent sets for that particular barrier.

$$I(B_i) = R(B_i) \cap A(B_i)$$

After developing the reachability, antecedent, and intersection sets for all the barriers, the extraction process is applied. In each iteration, the B_i with identical reachability and intersection sets are extracted. For instance, in the first iteration, any barrier(s) with the same reachability and intersection sets are categorized as the first group, securing their top-level position (Level I) in the ISM hierarchy structure. In the next iteration, the extracted barrier(s) in the previous iteration are excluded, and the procedure is repeated until the remaining barriers' hierarchy levels are established.

Step 6 – Formulation of the ISM Model. The structural model is developed from the final reachability matrix (FRM). Based on the level of attainment of the barriers, they are positioned in the structural model. Barriers of the first level are placed at the top, and barriers of subsequent lower levels are placed below. Next, a digraph is developed based on the relationships represented in the FRM. The transitive connections are omitted from the digraph. Next, the vector nodes are replaced with statements, and the digraph is converted to an ISM-based model, which is rechecked to ensure conceptual consistency.

3.5. Matrics d'Impacts Croises-Multiplication Applique a Classement (MICMAC) Analysis

In line with our third research objective, Matrics d'Impacts Croises-Multiplication Applique a Classement (MICMAC) was used to cluster the barriers based on their driving and dependence power (Rathore et al., 2022). While the driving power of a barrier is a summation of all the barriers influenced by it, the dependence power is the same for all the barriers affecting it. The Final Reachability Matrix (FRM) is used to determine these values; the driving and dependence power of a barrier is the sum of the row and column entries respectively where the barrier is positioned in the FRM. Each barrier can then be plotted on a two-dimensional graph having Dependence Power and Driving Power as the X and Y coordinates respectively; they can then correspond to one of the four quadrants (clusters) (Kumar et al., 2021; Rathore et al., 2022):

(1) *Autonomous (Quadrant I)* – Barriers in this quadrant have weak driving power and weak dependence power.

(2) *Dependent (Quadrant II)* – Barriers in this quadrant have weak driving power but strong dependence power.

(3) *Linkage (Quadrant III)* – Barriers in this quadrant have strong driving and dependence power.

(4) D*river or Independent (Quadrant IV)* – Barriers in this quadrant have strong driving power but weak dependence power.

4. Results

The results are presented as per the research objectives. First, the barriers identified from the literature and confirmed through stakeholder interviews are discussed. Next, the expert validation of these barriers through the FDT is explained. The different steps of the ISM technique used to model these barriers (as a hierarchical structure with interrelationships) is detailed in the following section, followed by presentation of the results of the MICMAC analysis involving clustering and prioritization of these barriers.

4.1. Barriers Identified using the Literature Review and Expert Interviews

Thirteen barriers to Industry 4.0 adoption in agricultural supply chains were identified at this stage. They are summarized in Table 3.

Table 3. List of barriers to Industry 4.0 adoption in agriculture

Barrier Category	Code	Barriers	Literature Source/s

Economic Barriers (ECB)	ECB1	High cost of implementation	Long et al. (2016); Masud et al. (2017); Kasemi et al (2022); Narwane et al. (2022)
	ECB2	Long/Uncertain Return on Investment	Das et al. (2019); Sayem et al. (2022); Horváth and Szabó (2019); Narwane et al. (2022)
	ECB3	Lack of access to funding/loans	Kwanmuang et al. (2020); Balana and Oyeyemi (2022)
Institutional /Regulatory Barriers (IRB)	IRB1	Lack of regulatory polices/legal framework	Long et al. (2016); Rathore et al. (2022); Hughes et al. (2019); Kwanmuang et. al (2020); Narwane et al. (2022)
	IRB2	Low government support	Sayem et al. (2022); Kumar et al. (2021)
Behavioural/ Psychological Barriers (BPB)	BPB1	Lack of knowledge and awareness of technologies	Long et al. (2016); Kumar et al. (2021)
	BPB2	Reluctance to change existing processes	Rathore et al. (2022); Srivetbodee and Igel (2021)
	BPB3	Lack of trust in the technologies	Rathore et al. (2022); Yadav et al. (2020)
	BPB4	Benefits of technologies are unclear	Das et al. (2019); Steeneveld and Hogeveen (2015)
Organizational Barriers (ORB)	ORB1	Lack of compatibility with traditional methods	Long et al. (2016) Yadav et al. (2020); Yadav et al. (2022); Narwane et al. (2022)
	ORB2	Technology is too complex to implement	Boursianis et al. (2022); Narwane et al. (2022)
	ORB3	Lack of required competencies/skills	Narwane et al. (2022); Gadekar et al. (2022); Yadav et al. (2020)
	ORB4	Lack of information about the technologies	Long et al. (2016)

4.1.1. Economic Barriers

4.1.1.1. High cost of implementation (ECB1)

Previous studies have reported the high cost of Industry 4.0 technologies as a significant barrier to their implementation in agricultural supply chains. This was seen to be the case for climate-smart agriculture technologies in Europe (Long et al., 2016), as also smart farming and precision agriculture technologies in Kosovo, where 53% of farmers were not using them for this reason (Kasemi et al., 2022). Similarly, Narwane et al. (2022) and Kumar et al. (2021) have reported high investment costs of IOT and Industry 4.0 technologies as barriers to their implementations in agri-food and agriculture respectively in the Indian context. This was echoed in our interviews as well: high cost was highlighted as one of the main barriers to technology adoption in the Mekong region, especially among small-scale farmers and processors. According to the interviewees, small-scale enterprises face challenges from asymmetric market power and (unlike large firms), do not have the bargaining power to negotiate with smart logistics technology providers. With their financial resources further depleted during the COVID-19 pandemic, this situation has become worse. As per one interviewee: *"The cost of adopting robotic automation technologies is too expensive, and hence we are continuing with our existing mechanized operations at the moment".* As per another: *“Small or medium farmers do not have enough funds to invest in these technologies” with a third one saying: “Farmers do not have the budget to buy the latest equipment”.*

4.1.1.2 Long/Uncertain Return on Investment (ROI) (ECB2)

Evidence from the literature suggests long or uncertain return on investment (ROI) from Industry 4.0 technologies being a significant barrier to the latter’s adoption. For example, Long et al. (2016) found the ROI periods of contemporary technologies in the European agricultural sector to be overly long, and hence a barrier. Similarly, in Das et al.’s (2019) study on smart farming technologies in Ireland, one-third of the participants (farmers) highlighted uncertain ROI to be the reason for their non-adoption of new technologies. Previous studies in manufacturing (Sayem et al., 2022; Horváth and Szabó, 2019) have also reported “uncertain return on investment” as a prominent barrier to Industry 4.0 adoption. According to one of the interviewees, “there needs to be clear ROI evidence to convince stakeholders to adopt latest technologies”. Similarly, another interviewee identified “high investment cost vis-a-vis return” to be a key issue.

4.1.1.3 Lack of access to funding/loans (ECB3)

According to the interviewees, the majority of farmers in Thailand and other Mekong Countries are small-scale; their access to funds and loans from financial institutions is therefore limited, which makes them less able to adapt to technology-oriented market disruptions. This is also supported by literature. For example, Kwanmuang et al.’s (2020) study on small-scale farmers in Thailand found lack of access to capital to be a barrier to (their) smart technology adoption. Similarly, OECD (2021) note that small-scale farmers have a lower ability to access capital (than large firms) due to factors such as limited credit history and lack of detailed financial information; the unmet financing needs of such small-scale enterprises in emerging markets is a whopping $5.2 trillion each year (IFC, 2017). Lack of access to funding/loans has been identified as a barrier to technology adoption in other developing countries like Nigeria also (Balana and Oyeyemi (2022).

4.1.2 Institutional/Regulatory Barriers

4.1.2.1. Lack of regulatory policies/legal framework (IRB1)

In many countries, the hesitancy to adopt Industry 4.0 technologies (e.g., Blockchain) in agriculture is due to the lack of appropriate regulations and legal framework (Yadav et al., 202; Rathore et al., 2022). For example, Long et al. (2016) highlighted several policy and regulatory issues acting as barriers for technology solution providers in Europe (to diffuse their innovations into the agricultural sector). Similarly, poor national policies were found to be the main barrier to the adoption of smart technologies in the Thai agricultural sector (Kwanmuang et al., 2020). Technologies like autonomous vehicles and equipment also require regulatory policies; for example, on issues such as vehicle licensing and liability requirements (Rathore et al., 2022). McKinsey (2012) also emphasizes that appropriate government policies can lead to successful adoption of contemporary technologies in developing countries. A few interviewees identified high import tariffs for Industry 4.0 technologies as a regulatory barrier; their concern is valid given that suppliers of these technologies are mostly based overseas. A lowering of these tariffs, especially in developing countries, could be a big enabler for farmers, agri-producers, and logistics service providers to import and apply innovative technologies in their operations.

4.1.2.2. Low government support (IRB2)

Most interviewees highlighted the importance of government financial support and incentives for Industry 4.0 adoption in the Mekong agricultural sector. The literature on agricultural supply chains also echoes these sentiments of government support and incentives being critical to Industry 4.0 adoption in the sector (Kumar et al., 2021). According to one interviewee, the government should partner with banks to provide interest-free/low-interest loans, while another highlighted the importance of government technical support and capacity-building programs for increasing Industry 4.0 adoption. Others suggested that the *"government should subsidize the cost of innovative technologies to facilitate adoption" or* should provide support for education and training to transform existing employees into digitally skilled ones. The other issue highlighted by the interviewees was the lack of digital infrastructure, which is a prerequisite for implementing some of the Industry 4.0 technologies. For example, the non/limited availability of internet infrastructure is a barrier to adopting technologies such as smart containers (where fast internet is needed for real-time monitoring and communication). Here again, the government should come forward to develop/support widespread and fast internet availability.

4.1.3 Behavioural/Psychological Barriers

4.1.3.1. Lack of Knowledge and awareness of technologies (BPB1)

It was evident from the interviewees that most of them, including the government ones, are not fully aware of the potential of Industry 4.0 technologies. Previous studies have also highlighted lack of knowledge and awareness of advanced technologies being a barrier to their adoption (Long et al., 2016; Kumar et al., 2021). As per the interviewees, this knowledge deficit is greater among small and medium-scale enterprises, where they don't know how to use, where to source from, and what the potential benefits of these technologies are, all of which hampers their (these technologies') adoption. In this context, some interviewees also highlighted the high knowledge-distance between the transferors (technology solution providers) and the transferees (farmers and processors). To build Industry 4.0 awareness, one of the interviewees advocated the use of related demos and case studies of successful implementations. As per another: *"All relevant stakeholders should conduct awareness programs on Industry 4.0 technologies, and also create a networking platform for stakeholders to raise queries on it and seek answers/solutions".*

4.1.3.2. Reluctance to change existing processes (BPB2)

The interviewees informed that most farmers and processors are using traditional methods and are reluctant to change them to accommodate new technologies. This reluctance was found to be greater among first-generation business owners, and which was appropriately captured in the words of one interviewee*: "For farmers who are old, it is hard for them to learn new things or change their habits".*

These findings find support from Srivetbodee and Igel (2021), where resistance to digital adoption was found to be related to age, with older farmers more uncomfortable/resistant to learn new technologies; also, resistance to change was found to be greater among successful business owners, who, given their success with existing approaches, were un-appreciative of the need for change. Previous studies have found that small farmers tend to resist the adoption of new technologies due to the greater perceived risk, and the financial burden associated with them (ERIA, 2019). According to the interviewees, taking the first step to (new) technology adoption is the most difficult, but once this happens, further incremental implementations come more naturally and easily. One of the participants highlighted the need to be open-minded to learn and adapt to new technological innovations.

4.1.3.3 Lack of trust in the technologies (BPB3)

Several participants highlighted the lack of trust in Industry 4.0 technologies as the main barrier to their adoption. It was evident from the interviews that distrust in technologies primarily stems from concerns about the longevity of the technologies and their ability to fulfill desired productivity goals. A few participants also raised concerns related to privacy and data security. This is largely due to the deep-rooted cultural preference for traditional methods among agricultural communities, leading to skepticism towards new technologies. One interviewee emphasized the importance of fostering trust in Industry 4.0 technologies by showcasing demos and instances of successful implementations that farmers can observe firsthand. This sentiment aligns with similar findings in existing literature (e.g., Rathore et al., 2022; Zkik et al., 2022; Akella et al., 2023), where a reported lack of trust in new technologies is identified as a barrier to adoption. For instance, Yadav et al. (2020) reported a lack of trust in Blockchain as a major barrier to its adoption in agricultural supply chains.

4.1.3.4 Benefits of technologies are unclear (BPB4)

According to some interviewees, the lack of clear cost-benefit information on Industry 4.0 technologies is a barrier to their adoption. As per one interviewee: "*To invest in new technology, farmers should have an understanding of the cost, income, and expenses*". Another interviewee stressed the need to create awareness of the tangible and intangible benefits, as well as the short and long-term benefits of Industry 4.0 technologies. Here intangible benefits include the increase in product value from the extension in shelf life, the lowering of process losses, and the reduction in sales discount (due to the improved quality and reputation) (Sharma et al., 2021). Previous studies have also reported unclear benefits of technology to be a barrier to its adoption (Shepherd et al., 2020; Steeneveld and Hogeveen, 2015).

4.1.4. Organizational Barriers

4.1.4.1. Lack of compatibility with traditional methods (ORB1)

It was evident from the interviews that the lack of compatibility of Industry 4.0 technologies with legacy systems/traditional methods was a barrier to their adoption. According to respondents, traditional agricultural methods may not be designed to integrate seamlessly with advanced technologies, requiring significant modifications or adaptations that can be complex and costly. Therefore, incorporating such technologies into existing traditional practices can disrupt established workflows and routines, potentially leading to reduced productivity and resistance among users. These concerns have also got support from literature. For example, Yadav et al. (2022) and Kumar et al. (2021) report compatibility with pre-existing hardware and software to be an issue when applying Industry 4.0 technologies. Similarly, as per Narwane et al. (2022), deployment of IoT-based wireless sensor networks (WSNs) at an agricultural farm demands a seamless exchange of data among different entities, people, and systems, which is only possible with good compatibility across systems and stakeholders.

4.1.4.2. Technology is too complex to implement (ORB2)

The perceived complexity of Industry 4.0 technology can cause anxiety and resistance to (its) adoption (Rathore et al., 2022). Interviewees highlighted some Industry 4.0 technologies to be too complex for most organizations. Evidence from the literature (e.g., Bolfe et al., 2020) also suggests adoption of a technology to be inversely proportional to its complexity. Similarly, Long et al. (2016) report overly complex technologies being barriers to innovations (environment-oriented) in agricultural supply chains.

4.1.4.3. Lack of required competencies/skills (ORB3)

Implementing Industry 4.0 technologies is challenging and if necessary, skills and competencies are not there, and more so, if farmers and enterprises wish to move from basic to more sophisticated implementation (UNESCAP, 2020). To thrive in a smart economy, enterprises need a diverse set of skills ranging from generic information and communications technology (ICT) skills to more specialist ones (e.g., how to program Apps, develop ICT applications and manage networks). However, such qualified and skilled employees are in short supply (Gadekar et al., 2022). Also, as evident from the interviews, many smallholder farmers are old, and with less formal education, which makes it difficult for them to apply any new technology without technical support. This is also evidenced in the literature with Yadav et al. (2020) finding farmers to be not very tech-savvy, and the understanding of Industry 4.0 technologies such as blockchain being difficult for them.

4.1.4.4 Lack of information about the technologies (ORB4)

It was clear from the interviews that the stakeholders, including the government entities in GMS countries, are not well aware of where to find useful information on Industry 4.0 technologies, as the sources are scattered and not easily accessible; also, that knowledge on these technologies, including their adoption is mostly shared through word-of-mouth, and hence susceptible to misinformation. A key reason for such accessibility issues in these (GMS) countries is the language barrier, or the so-called 'Cross-Language Information Access' issue: English is not the main language, but the majority of websites and most self-learning materials for technology adoption there are in English (that creates the information-related barriers (ERIA, 2019)). As per the agricultural sector literature also (e.g., Long et al., 2016), overly scientific language (jargon) is a barrier to the adoption of innovative technologies in the sector.

Now that we have identified and explained the 13 barriers, the next step is to validate them using the Fuzzy Delphi technique (FDT).

4.2. Validation of Industry 4.0 Adoption Barriers - Fuzzy Delphi Technique (FDT)

The FDT steps were applied as per Section 3.4 and the results from that are given in Table 4.

Table 4. Fuzzy Delphi Method (FDM) results

Codes	**Fuzzy Weights** $(a_{j,} b_{j,} c_j)$	**Defuzzification** (d_j)	**Result**
ECB1	(0.3, 0.72, 0.9)	0.64	Retained
ECB2	(0.1, 0.55, 0.9)	0.52	Retained
ECB3	(0.1, 0.64, 0.9)	0.55	Retained
IRB1	(0.1, 0.57, 0.9)	0.52	Retained
IRB2	(0.1, 0.55, 0.9)	0.52	Retained
BPB1	(0.1, 0.60, 0.9)	0.53	Retained
BPB2	(0.1, 0.56, 0.9)	0.52	Retained
BPB3	(0.1, 0.55 ,0.9)	0.52	Retained
BPB4	(0.1, 0.40, 0.7)	0.40	**Removed**
ORB1	(0.1, 0.57, 0.9)	0.52	Retained
ORB2	(0.1, 0.56 ,0.9)	0.52	Retained
ORB3	(0.1, 0.62, 0.9)	0.54	Retained
ORB4	(0.1, 0.59, 0.9)	0.53	Retained
	Threshold Value	**0.52**	

As seen in Table 4, all the barriers except BPB4 (Benefits of technology are unclear) are retained as their defuzzification weights are greater than or equal to the threshold value of 0.52; BPB4's weight on the other hand is much lower at 0.40, and which is therefore removed.

4.3. Understanding the hierarchical interrelationships between the barriers using ISM

ISM as per Section 3.5 was applied with the starting point being the 12 barriers identified from the FDT analysis (as above). Domain experts' inputs were first used to create the structural self-interaction matrix (SSIM) and the subsequent Initial Reachability Matrix (IRM) that are presented in Tables 5 and 6 below.

Table 5. Structural Self-Interaction Matrix (SSIM)

Codes	ORB4	ORB3	ORB2	ORB1	BPB3	BPB2	BPB1	IRB2	IRB1	ECB3	ECB2	ECB1
ECB1	O	A	A	A	O	V	O	A	O	A	V	-
ECB2	O	O	A	A	O	V	O	A	O	A	-	
ECB3	O	O	O	O	O	O	O	A	A	-		
IRB1	A	O	O	O	O	V	A	X	-			
IRB2	A	V	O	O	O	V	A	-				
BPB1	A	V	V	O	V	V	-					
BPB2	A	A	A	A	A	-						
BPB3	A	O	A	A	-							
ORB1	O	O	V	-								
ORB2	O	X	-									
ORB3	O	-										
ORB4	-											

Table 6. Initial Reachability Matrix (IRM)

Codes	ORB4	ORB3	ORB2	ORB1	BPB3	BPB2	BPB1	IRB2	IRB1	ECB3	ECB2	ECB1
ECB1	0	0	0	0	0	1	0	0	0	0	1	1
ECB2	0	0	0	0	0	1	0	0	0	0	1	0
ECB3	0	0	0	0	0	0	0	0	0	1	1	1
IRB1	0	0	0	0	0	1	0	1	1	1	0	0
IRB2	0	1	0	0	0	1	0	1	1	1	1	1
BPB1	0	1	1	0	1	1	1	1	1	0	0	0
BPB2	0	0	0	0	0	1	0	0	0	0	0	0
BPB3	0	0	0	0	1	1	0	0	0	0	0	0
ORB1	0	0	1	1	1	1	0	0	0	0	1	1
ORB2	0	1	1	0	1	1	0	0	0	0	1	1
ORB3	0	1	1	0	0	1	0	0	0	0	0	1
ORB4	1	0	0	0	1	1	1	1	1	0	0	0

Then after incorporation of transitivity in the Initial Reachability Matrix (IRM), the Final Reachability Matrix (FRM) was developed which is presented in Table 7 below.

Table 7. Final Reachability Matrix (FRM)

Codes	ORB4	ORB3	ORB2	ORB1	BPB3	BPB2	BPB1	IRB2	IRB1	ECB3	ECB2	ECB1	Driving Power	*Rank*
ECB1	0	0	0	0	0	1	0	0	0	0	1	1	3	*7*
ECB2	0	0	0	0	0	1	0	0	0	0	1	0	2	*8*
ECB3	0	0	0	0	0	1*	0	0	0	1	1	1	4	*6*
IRB1	0	1*	0	0	0	1	0	1	1	1	1*	1*	7	*4*
IRB2	0	1	1*	0	0	1	0	1	1	1	1	1	8	*3*
BPB1	0	1	1	0	1	1	1	1	1	1*	1*	1*	10	*2*
BPB2	0	0	0	0	0	1	0	0	0	0	0	0	1	*9*
BPB3	0	0	0	0	1	1	0	0	0	0	0	0	2	*8*
ORB1	0	1*	1	1	1	1	0	0	0	0	1	1	7	*4*
ORB2	0	1	1	0	1	1	0	0	0	0	1	1	6	*5*
ORB3	0	1	1	0	1*	1	0	0	0	0	1*	1	6	*5*
ORB4	1	1*	1*	0	1	1	1	1	1	1*	1*	1*	11	*1*
Dependence Power	1	7	6	1	6	12	2	4	4	5	10	9	67/67	
Rank	*9*	*4*	*5*	*9*	*5*	*1*	*8*	*7*	*7*	*6*	*2*	*3*		

**Denotes the values which are changed from "0" to "1" during transitivity check*

The FRM was then partitioned to establish the hierarchy level of the barriers, and this is done through multiple iterations. Tables 8-15 show the level partitioning of barriers.

Table 8. Level Partitioning (Iteration 1)

Factors	**Reachability Set**	**Antecedent Set**	**Intersection Set**	**Level**
ECB1	BPB2; ECB2; ECB1	ECB1; ECB3; IRB1; IRB2; BPB1; ORB1; ORB2; ORB2; ORB4	ECB1	
ECB2	ECB2; BPB2	ECB1; ECB2; ECB3; IRB1; IRB2; BPB1; ORB1; ORB2; ORB3; ORB4	ECB2	

ECB3	BPB2; ECB3; ECB2; ECB1	ECB3; IRB1; IRB2; BPB1; ORB4	ECB3	
IRB1	ORB3; ORB2; ORB1; BPB3; BPB2; BPB1; IRB2; IRB1; ECB3; ECB2; ECB1	IRB1; IRB2; BPB1; ORB4	IRB1; IRB2; BPB1	
IRB2	ORB3; ORB2; ORB1; BPB3; BPB2; BPB1; IRB2; IRB1; ECB3; ECB2; ECB1	IRB1; IRB2; BPB1; ORB4	IRB1; IRB2; BPB1	
BPB1	ORB3; ORB2; ORB1; BPB3; BPB2; BPB1; IRB2; IRB1; ECB3; ECB2; ECB1	BPB1; ORB4	BPB1	
BPB2	BPB2	ECB1; ECB2; ECB3; IRB1; IRB2; BPB1; BPB2; BPB3; ORB1; ORB2; ORB3; ORB4	BPB2	I
BPB3	BPB2; BPB3	BPB1; BPB3; ORB1; ORB2; ORB3; ORB4	BPB3	
ORB1	ORB3; ORB2; ORB1; BPB2; BPB3; ECB2; ECB1	ORB1	ORB1	
ORB2	ORB3; ORB2; BPB2; BPB3; ECB2; ECB1	IRB2; ORB1; ORB2; ORB3; ORB4	ORB3; ORB2	
ORB3	ORB3; ORB2; BPB3; BPB2; ECB2; ECB1	IRB1; IRB2; ORB1; ORB2; ORB3; ORB4	ORB3; ORB2	
ORB4	ORB4; ORB3; ORB2; BPB3; BPB2; BPB1; IRB2; IRB1; ECB3; ECB2; ECB1	ORB4	ORB4	

Table 9. Level Partitioning (Iteration 2)

Factors	Reachability Set	Antecedent Set	Intersection Set	Level
ECB1	ECB2; ECB1	ECB1; ECB3; IRB1; IRB2; BPB1; ORB1; ORB2; ORB2; ORB4	ECB1	
ECB2	ECB2	ECB1; ECB2; ECB3; IRB1; IRB2; BPB1; ORB1; ORB2; ORB3; ORB4	ECB2	II
ECB3	ECB3; ECB2; ECB1	ECB3; IRB1; IRB2; BPB1; ORB4	ECB3	
IRB1	ORB3; ORB2; ORB1; BPB3; BPB1; IRB2; IRB1; ECB3; ECB2; ECB1	IRB1; IRB2; BPB1; ORB4	IRB1; IRB2; BPB1	
IRB2	ORB3; ORB2; ORB1; BPB3; BPB1; IRB2; IRB1; ECB3; ECB2; ECB1	IRB1; IRB2; BPB1; ORB4	IRB1; IRB2; BPB1	
BPB1	ORB3; ORB2; ORB1; BPB3; BPB1; IRB2; IRB1; ECB3; ECB2; ECB1	BPB1; ORB4	BPB1	
BPB3	BPB3	BPB1; BPB3; ORB1; ORB2; ORB3; ORB4	BPB3	II
ORB1	ORB3; ORB2; ORB1; BPB3; ECB2; ECB1	ORB1	ORB1	
ORB2	ORB3; ORB2; BPB3; ECB2; ECB1	IRB2; ORB1; ORB2; ORB3; ORB4	ORB3; ORB2	
ORB3	ORB3; ORB2; BPB3; ECB2; ECB1	IRB1; IRB2; ORB1; ORB2; ORB3; ORB4	ORB3; ORB2	
ORB4	ORB4; ORB3; ORB2; BPB3; BPB1; IRB2; IRB1; ECB3; ECB2; ECB1	ORB4	ORB4	

Table 10. Level Partitioning (Iteration 3)

Factors	Reachability Set	Antecedent Set	Intersection Set	Level
ECB1	ECB1	ECB1; ECB3; IRB1; IRB2; BPB1; ORB1; ORB2; ORB2; ORB4	ECB1	III
ECB3	ECB3; ECB1	ECB3; IRB1; IRB2; BPB1; ORB4	ECB3	
IRB1	ORB3; ORB2; ORB1; BPB1; IRB2; IRB1; ECB3; ECB1	IRB1; IRB2; BPB1; ORB4	IRB1; IRB2; BPB1	
IRB2	ORB3; ORB2; ORB1; BPB1; IRB2; IRB1; ECB3; ECB1	IRB1; IRB2; BPB1; ORB4	IRB1; IRB2; BPB1	
BPB1	ORB3; ORB2; ORB1; BPB1; IRB2; IRB1; ECB3; ECB1	BPB1; ORB4	BPB1	

ORB1	ORB3; ORB2; ORB1; ECB1	ORB1	ORB1
ORB2	ORB3; ORB2; ECB1	IRB2; ORB1; ORB2; ORB3; ORB4	ORB3; ORB2
ORB3	ORB3; ORB2; ECB1	IRB1; IRB2; ORB1; ORB2; ORB3; ORB4	ORB3; ORB2
ORB4	ORB4; ORB3; ORB2; BPB1; IRB2; IRB1; ECB3; ECB1	ORB4	ORB4

Table 11. Level Partitioning (Iteration 4)

Factors	Reachability Set	Antecedent Set	Intersection Set	Level
ECB3	ECB3	ECB3; IRB1; IRB2; BPB1; ORB4	ECB3	IV
IRB1	ORB3; ORB2; ORB1; BPB1; IRB2; IRB1; ECB3	IRB1; IRB2; BPB1; ORB4	IRB1; IRB2; BPB1	
IRB2	ORB3; ORB2; ORB1; BPB1; IRB2; IRB1; ECB3	IRB1; IRB2; BPB1; ORB4	IRB1; IRB2; BPB1	
BPB1	ORB3; ORB2; ORB1; BPB1; IRB2; IRB1; ECB3	BPB1; ORB4	BPB1	
ORB1	ORB3; ORB2; ORB1	ORB1	ORB1	
ORB2	ORB3; ORB2	IRB2; ORB1; ORB2; ORB3; ORB4	ORB3; ORB2	IV
ORB3	ORB3; ORB2	IRB1; IRB2; ORB1; ORB2; ORB3; ORB4	ORB3; ORB2	IV
ORB4	ORB4; ORB3; ORB2; BPB1; IRB2; IRB1; ECB3	ORB4	ORB4	

Table 12. Level Partitioning (Iteration 5)

Factors	Reachability Set	Antecedent Set	Intersection Set	Level
IRB1	ORB1; BPB1; IRB2; IRB1	IRB1; IRB2; BPB1; ORB4	IRB1; IRB2; BPB1	
IRB2	ORB1; BPB1; IRB2; IRB1	IRB1; IRB2; BPB1; ORB4	IRB1; IRB2; BPB1	
BPB1	ORB1; BPB1; IRB2; IRB1	BPB1; ORB4	BPB1	
ORB1	ORB1	ORB1	ORB1	V
ORB4	ORB4; BPB1; IRB2; IRB1	ORB4	ORB4	

Table 13. Level Partitioning (Iteration 6)

Factors	Reachability Set	Antecedent Set	Intersection Set	Level
IRB1	BPB1; IRB2; IRB1	IRB1; IRB2; BPB1; ORB4	IRB1; IRB2; BPB1	VI
IRB2	BPB1; IRB2; IRB1	IRB1; IRB2; BPB1; ORB4	IRB1; IRB2; BPB1	VI
BPB1	BPB1; IRB2; IRB1	BPB1; ORB4	BPB1	
ORB4	ORB4; BPB1; IRB2; IRB1	ORB4	ORB4	

Table 14. Level Partitioning (Iteration 7)

Factors	Reachability Set	Antecedent Set	Intersection Set	Level
BPB1	BPB1	BPB1; ORB4	BPB1	VII
ORB4	ORB4; BPB1	ORB4	ORB4	

Table 15. Level Partitioning (Iteration 8)

Factors	Reachability Set	Antecedent Set	Intersection Set	Level
ORB4	ORB4	ORB4	ORB4	VIII

The ISM model that is developed at the end from the FRM is presented in Figure 4.

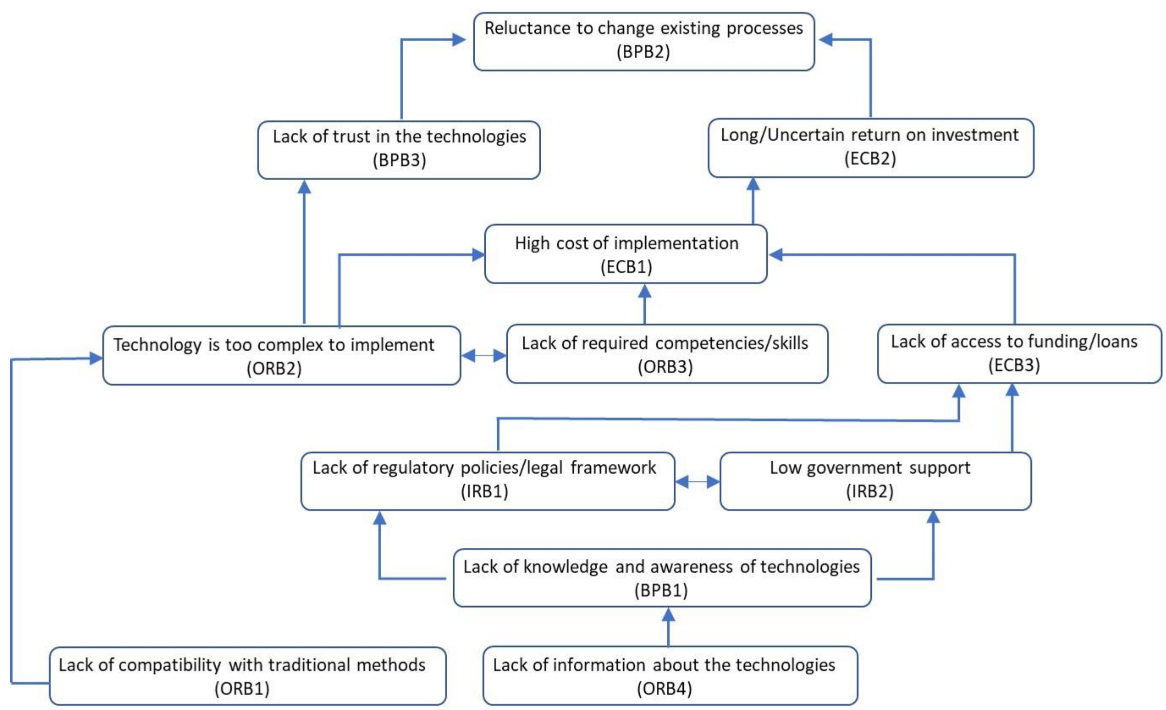

Figure 4. ISM-based Structural Model

4.4. Understanding the Driving and Dependence power of barriers using MICMAC Analysis

The Final Reachability Matrix (FRM) was used to calculate the driving and dependence powers for each of the barriers (refer Table 7 presented earlier). These are plotted in a 2-dimensional plot with dependence power and driving power as the X and Y coordinates (refer figure 5 below).

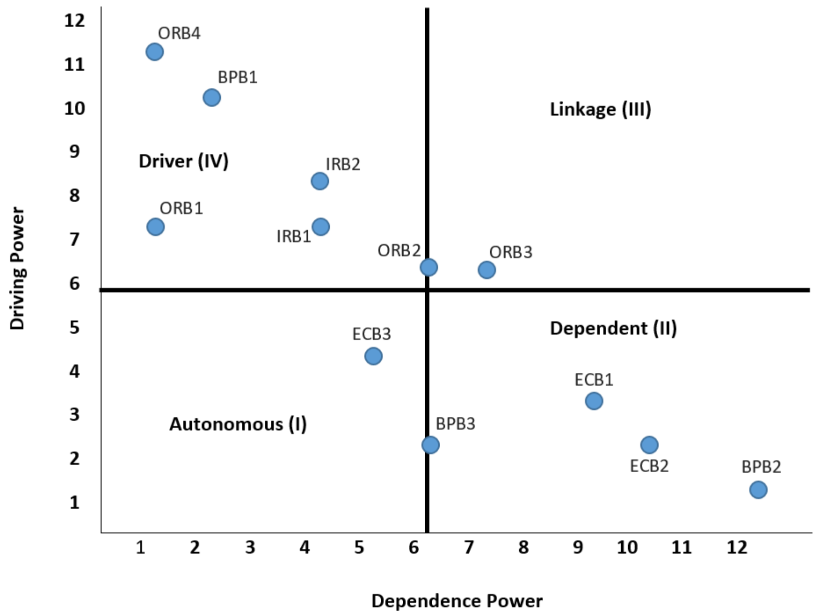

Figure 5. Clustering of barriers using MICMAC Analysis

5. Discussion

In line with our first research objective, the study identified 13 barriers to Industry 4.0 adoption in agricultural supply chains. These barriers were further categorized into four groups, namely economic barriers, institutional barriers, behavioral/psychological barriers, and organizational barriers. They were then assessed using the Fuzzy Delphi Technique, where the “Benefits of technologies are unclear” (BPB4) barrier was eliminated. This elimination could be because of its overlap with the “lack of knowledge and awareness of technologies” (BPB1) and the “uncertain/long return on investment” (ECB2) barriers. The rest of the barriers were validated and retained for further analysis. Such an in-depth determination of Industry 4.0 adoption barriers in agricultural supply chains is a significant contribution, given that it has not been previously attempted for a large, multi-country, emerging economy context.

Next, in line with our second research objective, the ISM approach revealed the hierarchical structure and precedence relationships among the barriers (see Figure 4). Then, as per our third research objective, the barriers were clustered into four distinct categories: Autonomous, Dependent, Linkage, and Driver barrier categories (see Figure 5). As evident from figures 4 and 5, the five Driver category barriers (Driver (IV)) occupy the three lowest levels in the ISM hierarchical model and influence the other barriers. These are “lack of information about the technologies” (ORB4), “lack of compatibility with traditional methods” (ORB1), “lack of knowledge and awareness of technologies” (BPB1), “lack of regulatory policies/legal framework” (IRB1), and “low government support” (IRB2). They influence the other barriers and are therefore considered the most important. Among these, two of them (ORB4 and ORB1) occupy the base or the lowest level of the ISM model. This means they are independent barriers which directly and indirectly influence all the other ones, and therefore require serious attention from the policymakers. Prior studies indicate that a lack of information about new technologies can lead to fragmented and disorganized adoption (Long et al., 2016). One respondent pointed out that literacy rates among farmers, especially those using traditional methods, tend to be low. As a result, accessing, understanding, and utilizing information related to new technologies can be particularly challenging for them. Moreover, a lack of internet access, predominantly in rural areas, can significantly hinder access to information about new technologies. In parallel, incompatibility with existing technologies emerges as a major barrier, amplifying other barriers. One interviewee cited the absence of essential infrastructure, such as reliable internet access, especially in remote and rural areas, as a factor impeding the adoption of Industry 4.0 technologies. Several pieces of literature also recognize these compatibility issues with existing systems as concerns affecting the adoption of new technologies (Long et al., 2016; Yadav et al., 2020; 2022; Narwane et al., 2022).

The "Technology is too complex to implement" (ORB2), and "lack of required competencies/skills (ORB3) barriers emerged as the Linkage barriers (Quadrant III) that occupy the mid-level in the ISM model. These barriers are therefore sensitive/unstable, and must be addressed carefully, as any action involving them would result in a subsequent reaction that can affect them as well as the other barriers. Existing literature reveals that stakeholders in the agricultural sector, including small-scale farmers, often perceive Industry 4.0 technologies as too complex to implement and manage (Boursianis et al., 2022; Narwane et al., 2022). However, evidence from other sectors indicates that the perceived complexity of these technologies as a barrier to adoption is not exclusive to agriculture. For instance, studies from the logistics sector show that firms often prefer working with simpler software platforms over more complex and advanced blockchain-based platforms (Rathore et al., 2022). The lack of necessary competencies and skills is another barrier consistently highlighted across various sectors in Industry 4.0 literature. Within agriculture, practitioners, especially those accustomed to traditional farming methods, may lack the essential skills and understanding to effectively utilize advanced technologies (Narwane et al., 2022; Yadav et al., 2020). Similarly, in sectors like supply chain management, the absence of skilled and trained staff to operate modern equipment and IT systems is identified as a significant barrier to adopting new technologies (Sharma et al., 2021).

Four barriers, namely "high cost of implementation" (ECB1), "long/uncertain return on investment" (ECB2), "lack of trust in the technologies" (BPB3), and "reluctance to change existing processes" (BPB2) emerged as Dependent barriers (Quadrant II). Not surprisingly, they occupy the top three hierarchical levels in the ISM model as the other barriers influence them. Of these, the "reluctance to change existing processes" barrier occupies the highest level in the ISM hierarchy, which means it is directly and indirectly affected by all the other barriers and can only be managed by addressing them. Several studies categorize this obstacle as a behavioral/psychological barrier in the agricultural sector, influenced collectively by other barriers (Rathore et al., 2022; Srivetbodee and Igel, 2021). For instance, distrust in technologies can lead to reluctance in adopting Industry 4.0 technologies. Unsurprisingly, multiple studies identify lack of trust as a significant barrier in the agricultural sector, affected by other barriers (Rathore et al., 2022; Yadav et al., 2020). In fact, the literature provides substantial evidence that lack of trust is a prevalent concern across various industries. For example, in the logistics sector, lack of trust was found to have higher dependence power than other barriers concerning the adoption of disruptive technologies (Rathore et al., 2022), mirroring findings of this study. Similarly, uncertainty in return on investments is not only a substantial barrier in agriculture (Das et al., 2019; Sayem et al., 2022; Horváth and Szabó, 2019; Narwane et al., 2022) but is also prevalent in other sectors. Gadekar et al. (2022), for example, identified uncertain return on investments as a barrier in the Indian manufacturing industry. Regarding the high cost of implementation, it is universally recognized as a barrier to adopting Industry 4.0 technologies across sectors, including agriculture (Long et al., 2016; Masud et al., 2017; Kasemi et al, 2022; Narwane et al., 2022). The construction industry also reports high costs as an obstacle to transitioning towards off-site construction such as additive manufacturing (Gan et al., 2018).

Finally, “lack of access to funding/loans” emerged as an autonomous barrier (Quadrant I). Barriers falling under this category have weak driving and dependence power, and therefore less impact on adoption (of Industry 4.0 technologies in this case); they can also be tackled relatively easily.

Next, a closer examination of the direct causal relationships among the barriers shows that “lack of information about the technologies” is the main reason for “stakeholders' lack of knowledge and awareness” about them. As discussed earlier, low English proficiency is a problem for farmers in the GMS region; moreover, different countries in the region speak different languages. Hence, there is a need to provide information related to Industry 4.0 technologies in the local language. The manuals and training materials that are typically in English should also be converted to the local language. Addressing this (lack of knowledge and awareness) issue is important, as it affects policy maker and government support and actions. As evidenced from the interviews, governments in the region, such as the Ministry of Agriculture and industry associations (who influence policy) have limited knowledge and awareness of Industry 4.0 technologies; for instance, many stakeholders are unaware of the intangible benefits of technology.

On the other hand, the “lack of compatibility with traditional methods or interoperability with existing systems” makes new technology adoption too complex for many stakeholders. It requires changing the current processes and systems (to accommodate the new technologies), which is considered risky and time-consuming. It also requires skilled and competent employees in those technologies who may be in short supply or expensive. Even if available, many small-scale enterprises may be unable to afford them in full-time mode because of their financial constraints (ERIA, 2019). One approach could be to upskill/reskill the low-skilled employees there. Government bodies, industry associations in partnership with banks, and other regional stakeholders could design appropriate capacity-building programs, and thereby play a key role in this.

The “high cost of implementation” is seen to cause the “long/uncertain return on investment” on Industry 4.0 technologies. To address this, local governments could give micro, small and medium-sized agricultural firms financial support in the form of credit guarantees, longer repayment periods, collateral-free loans, low/zero interest loans and subsidies. They could also work with local and regional banks, such as the Asian Development Bank (ADB) to facilitate easy access to finance for the agricultural sector. Selected technology products could also be exempt from import duties or could be heavily subsidized. A low or zero upfront cost model (OPEX model) could also be promoted. Next, the complex nature of some Industry 4.0 technologies (ORB2) is seen to cause a “lack of trust or confidence in using these technologies” (BPB3), mainly due to a perceived risk of failure. Then the “lack of trust or confidence in using these technologies” (BPB3) together with “long/uncertain return on investment” (or financial benefits) (ECB2) makes stakeholders “Reluctant to change their existing processes (to implement new technologies)” (BPB2).

6. Study Implications

The implications of this study are manifold. They can be categorized as research and practical implications.

6.1. Research Implications

In terms of research contributions, this study stands as the first exhaustive multi-method empirical investigation aimed at identifying, validating, and modeling the various barriers to Industry 4.0 adoption within the agricultural sector across multiple emerging countries. Consequently, the presented structural model addressing barriers to Industry 4.0 adoption in agriculture is both novel and significant. While this research is centered on GMS, the similarities in the foundational challenges encountered by the agricultural sectors in other emerging countries, especially in Asia, suggest that the insights derived from this study have broader applicability. The developed model could substantively facilitate subsequent research endeavors in this field, offering a basis for testing and application in diverse agricultural contexts. Furthermore, this research enriches the wider discourse on the barriers to adopting technological innovations in emerging nations, with a particular focus on Industry 4.0 adoption. Methodologically, the use of the Fuzzy Delphi-ISM approach in this study augments the body of work on multi-criteria decision-making frameworks and can serve as a useful model and benchmark for similar studies probing the barriers to Industry 4.0 adoption.

6.2. Practical Implications

This study provides practical insights that are instrumental for policymakers and agriculture supply chain stakeholders in devising new strategies and policy interventions to prioritize and address the barriers to Industry 4.0 technologies. The timeliness of this study is emphasized by the pivotal role of Industry 4.0 in the post-COVID recovery of the agricultural sector in emerging countries, and its potential to tackle inherent sectoral challenges such as labor shortages and unpredictable climatic conditions. Given that agriculture constitutes the economic backbone of GMS economies, accounting for 30% of employment in Thailand and Cambodia, 40% in Vietnam, over 50% in Myanmar, and 69% in Laos (ADB, 2021), the implications of this study are substantial. By addressing barriers to enhance Industry 4.0 adoption, this study can facilitate productivity gains, income boosts, and process cost reductions, contributing significantly to improving socio-economic conditions in these regions.

From a policy perspective, this study advocates for the formulation of clear policies, regulations, and guidelines to overcome barriers to the adoption of Industry 4.0 technologies. Governmental interventions, through well-framed regulations and policies, can act as catalysts for adopting these technologies by establishing supportive legal and institutional frameworks, offering financial incentives, and creating an environment conducive to digital transformation. Governments are encouraged to establish task forces to define standards and technical regulations for the application and dissemination of these technologies and to extend financial support, particularly to micro and small-scale enterprises, to foster the adoption of Industry 4.0 technologies. This research underscores the importance for governments to cultivate robust partnerships with banks and the private sector to enable fruitful public-private partnerships for the adoption of Industry 4.0 technologies.

7. Conclusions

Agricultural supply chains have traditionally relied on labor-intensive low-technology methods, with consequential low efficiencies and significant wastages. These deficiencies are now sought to be addressed through the incorporation of different Industry 4.0 technologies, and associated business model/operations transformations (De Clercq et al., 2018; World Economic Forum, 2022). A sustained, large-scale diffusion of these technologies requires the associated barriers to be addressed, which in turn requires an in-depth and structured understanding of these barriers first, which was the primary focus of this study.

This study stands as one of the first studies to examine the barriers encountered in adopting Industry 4.0 technologies within agricultural supply chains, especially in emerging economies. By employing an integrative Fuzzy Delphi-ISM approach and MICMAC analysis, it has delved deep into understanding the hierarchical structure and intricate interrelations among the barriers. Lack of information about technologies and lack of compatibility with traditional methods emerged as the two main barriers which directly and indirectly influence the other ones.

Though the study is rigorous, it does have some limitations. First, the identified list of 13 barriers may not be exhaustive. Future studies can look at updating them for different contexts. Second, the ISM methodology uses binary relationships between the variables, i.e., in 0/1 terms. This is a limitation given that there could be an intermediate value between 0 and 1. Future researchers could therefore use other multi-criteria decision methodologies such as fuzzy DEMATEL or AHP for modeling the barriers. Finally, the weighting of the barriers in the Fuzzy Delphi technique as well as for the modelling is based on experts' subjective assessment. Because it is qualitative, the strength of the relationships among the barriers couldn't be assessed. Future research could therefore use a large-scale survey and structural equation modeling to hypothesize and statistically test the causal relationships among the barriers. Despite these limitations, we believe the proposed model and its successful application will significantly enhance the understanding of Industry 4.0 adoption barriers in the agricultural sector; will also encourage more research on this important topic.

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Appendices

Appendix A. Details of the experts interviewed

Participant	Stakeholder	Organization Focus	Designation	Country
P1	Government	Ministry of Agriculture	Head, Agricultural Promotion	Thailand
P2	Association (Export)	Thai Rice Exporter Association	President	Thailand

Participant	Stakeholder	Organization Focus	Designation	Country
P3	Private Firm	Rice Mill / Rice exporter	Managing Director	Thailand
P4	Private Firm	Rice Mill / Rice exporter	Vice President	Cambodia
P5	Industry Association	Thai Fruit Export Association	President	Thailand
P6	Private Firm	Tapioca Food Processing Firm	Managing Director	Thailand
P7	Private Firm	Logistics company (Reefer Container)	Managing Director	Thailand
P8	Private Firm	Logistics Company (Transportation)	Executive Director	Cambodia
P9	Private Firm	Warehousing and Cold Storage	General Manager	Thailand
P10	Association (Transportation)	GMS-Freight Transport Association	Vice Chairman	GMS
P11	Private Firm	Logistics Company (3PL/Transportation)	Managing Director	Thailand
P12	Private Firm	Logistics Company (Transportation)	Executive Vice President - Transportation and logistics	Thailand
P13	Private Firm	Cold Storage/Refrigeration Equipment Manufacturer	Thailand Country Representative	China/ Thailand
P14	Private Firm (Multinational)	Logistics and Supply Chain	General Manager (Thailand)	Global/ Thailand
P15	Private Firm	Renewable Energy Technologies	Design & Sales Engineer	Global/ Thailand
P16	Private Firm	Warehousing and Logistics (Chiller storage and Reefer Container)	Manager	Mekong Region
P17	Private Firm	Drone Manufacturer	CEO	Thailand
P18	Private Firm	Robotics and Drone Solution Provider	Co-founder and CEO	Thailand
P19	Private Firm (Multinational)	Warehouse Drone and Robotics	Business Development Manager	Singapore/ Global
P20	Private Firm (Multinational)	Smart warehouse and Robotic Automation Solution Provider	Operations Manager	Singapore
P21	Private Firm	Hydrokinetic Energy Technologies for Aquaculture	COO	Singapore

Appendix B. Details of Experts who Participated in FDT and ISM

Participant	Stakeholder	Organization Focus	Designation	Country
E1	Government	Horticulture and Subsidiary Crops Division – Ministry of Agriculture Forestry and Fisheries	Vice Chief	Cambodia
E2	Government	Plant Protection Division - Ministry of	Officer	Cambodia

Participant	Stakeholder	Organization Focus	Designation	Country
		Agriculture Forestry and Fisheries		
E3	Government	Agricultural Extension Division - Ministry of Agriculture Forestry and Fisheries	Officer	Cambodia
E4	Government	Ministry of Industry, Science, Technology & Innovation	Officer	Cambodia
E5	University	Department of Natural Resource Management and Development	Academic/Researcher	Cambodia
E6	University	Planning and International Cooperation – Agricultural University	Academic/Researcher	Cambodia
E7	Government	Ministry of Commerce	Director	Cambodia
E8	Private Firm	Food Production & Processing	Director	Cambodia
E9	Government	Information Technology and Innovation Division - Ministry of Industry and Commerce	Head of Division	Lao PDR
E10	University	Department of Agricultural Engineering	Academic/Researcher	Myanmar
E11	Government	Ministry of Electric Power	Director	Myanmar
E12	Government	Ministry of Agriculture, Livestock and Irrigation	Officer	Myanmar
E13	Association	International Freight Forwarders' Association	Director	Myanmar
E14	Association	Fruit, Flower and Vegetable Producers and Exporters Association	Director	Myanmar
E15	Private Firm	Logistics Company	CEO	Myanmar
E16	Research Firm	Horticultural Research Institute (Plant Protection)	Researcher	Vietnam
E17	University	National University of Forestry	Academic/Researcher	Vietnam
E18	Research Firm	Plant Protection Department – Rice Research Institute	Researcher	Vietnam
E19	University	Agro-Forestry-Fisheries – Quality Assurance Department	Officer	Vietnam
E20	Research Firm	Rice Research Institute	Head	Vietnam
E21	University	Department of Agriculture	Researcher	Thailand
E22	Private Firm	Social Enterprise	Managing Director	Thailand
E23	Government	Ministry of Agriculture and Cooperatives – Department of Agriculture Extension	Researcher	Thailand