

Barriers to the Adoption of Industry 4.0 Technologies in the Digital Agri-Food Supply Chain

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Abstract

Food waste in the agricultural sector remains a critical challenge with far-reaching impacts for food security and resource efficiency. In response, digitalization has increasingly been integrated into the Agri-Food Supply Chain (AFSC) to ease these losses. However, before effective digital solutions can be implemented, it is essential to identify and cognize the barriers within the digital AFSC. Only then can meaningful strategies be developed to overcome these obstacles. This study delineates the barriers and consequences of Industry 4.0 technologies in the AFSC through an analysis of current literature and expert perspectives. A total of 18 barriers were identified across the technical, operational, organizational and strategic dimensions. We use both the Matrix of Cross-Impact-Multiplication Applied to a Classification (MICMAC) method and interpretive structural modelling (ISM) to model these barriers. The results suggest that security and privacy concerns, technological immaturity, lack of technological infrastructure, high initial costs, uncertainty in Return On Investment (ROI), and lack of government regulation are the most important driving barriers within the hierarchical structure. Consequently, this research focuses on constraints that have emerged in the digital AFSC. This study serves as a guide for addressing supply chain issues in the Indian agri-food sector amid high demand for agricultural products.

Keywords- Interpretive structural modeling, Fuzzy-MICMAC analysis, Industry 4.0, Agri-food supply chain.

1. Introduction

The agriculture and food industry is intricate, encompassing a wide array of operations and participants worldwide. This sector is essential for supplying consumers with sustainable, adequate, affordable, and safe food, feed, nutrition, and energy resources, thereby supporting local economies and communities (Wolfert et al., 2017). Stakeholders within Agri-Food Supply Chains (AFSC) are being pushed hard to free trade policies and globalization, alongside demands for safe, sanitary, and high-quality food products (Zhao et al., 2024b). The increasing consumer demands for transparency and ethical sourcing are compelling businesses to change their operations (Zhao et al., 2019). A successful Supply Chain (SC) is primarily attained through socioeconomic and environmental factors affecting not only production itself, but also the well-being and health of communities and nature. As the industry shifts, innovation, collaboration, and sustainability should be of great concern in addressing upcoming barriers.

Agriculture has evolved in many ways throughout the current industrial revolutions. It was based on manual labour, people in the field, harvesting crops manually. Then machines followed, and it is time to enter the age of precision farming (Sargani et al., 2025). Consequently, there has been an improvement in farming activities, and producers have the capacity to satisfy the global food requirements. Despite industrial agriculture having boosted production many times, it has further aggravated a number of pre-existing problems, including environmental degradation, monoculture and loss of biodiversity. In the revolutionary era of Industry 4.0 (I4.0), the interrelation between interior and exterior environments becomes more evident, and the development of farming processes requires sustainability and flexibility.

The introduction of critical business processes, which are essential to I4.0, throughout the industry is changing fast, with intriguing prospects that have the potential to redefine agriculture in the future. Modern technologies such as Artificial Intelligence (AI), machine learning, cloud computing, big data and analytics, blockchain, automation, robotics, and the Internet of Things (IoT) are transforming a great number of spheres, including agriculture, providing the ease of gathering data, conducting operations, and decision-making (Zhao et al., 2024a). Since it is a complex process, digitalization of the SC management is particularly advantageous, as it enables tracking and transparency during the production process (Yadav et al., 2020). Research shows that a SC based on technology is capable of reducing the cost of a company by approximately 30%, enhancing its speed, agility, accuracy, and efficiency by nearly 70 % and minimizing inventory levels of an organization by almost 70% (Zhao et al., 2024c). This digitization plays a very important role in enabling farmers to respond quickly to market changes and to consumer demands. The incorporation of I4.0 digital technologies into the AFSC is no longer merely a trend; rather, it is a necessity driven by the increasing stress on planetary systems. The industry can use new technologies such as AI, big data analytics, and IoT to become more sustainable and efficient in the future. These technologies help streamline operations, assist individuals in making better decisions, and make operations smarter in various aspects. These novel concepts ensure that the work is much more productive, address serious environmental concerns, and reduce the carbon footprint of the entire ecosystem (Sharma et al., 2024; Tseng et al., 2019; Yadav et al., 2020).

To achieve these advantages, there is a need to focus on overcoming several obstacles, including one in the form of financial constraints. Limited funding continues to pose a serious challenge to many agricultural businesses, since they might not have the funds required to invest in new technologies. Moreover, technical skills are heavily unevenly distributed across the workforce, and it is hard to implement and operate such sophisticated systems within these systems. Also, regulatory difficulties may contribute, as current policies may not fully endorse or even facilitate the implementation of novel strategies (Wolfert et al., 2017).

This research explores how I4.0 technologies can enhance the sustainability of agribusiness, focusing specifically on the Indian AFSC. It highlights key approaches, including smart farming technologies, data-driven decision-making, and sustainable SC management, to reduce waste, improve resource efficiency, and lower greenhouse gas emissions (Kazancoglu et al., 2021). It explores the potential of technology to enhance transparency in food production traceability, helping consumers feel confident in the safety of their food.

The previous literature suggests that I4.0 will significantly transform agri-food production and consumption in the near future. Achieving equitable and sustainable food systems requires effective collaboration among key stakeholders (Wolfert et al., 2017). The digital AFSC has interconnected barriers; therefore, identifying hierarchical links and hidden linkages requires a systematic approach. In this context, ISM can help organize complex barriers into levels, while Fuzzy-MICMAC can help evaluate their driving and dependence power under uncertainty. For systematic analysis, the combined ISM–Fuzzy MICMAC technique is used.

The focus of this research is to identify the key barriers of integrating I4.0 innovations into the digital AFSC, with a focus on sustainability. The research objectives (RO) are primarily:

RO1: Identify the barriers to adopting I4.0 technologies in the digital agri-food supply chain.

RO2: Evaluate the role of I4.0 in achieving sustainability goals in agri-food supply chain.

RO3: To evaluate the hierarchical interrelationships and driving-dependence power among these identified barriers.

The Section 1 of the study is an introduction to the context. Section 2 discusses the literature and identifies the main problems. It then describes the study's design and approach, namely the ISM and Fuzzy-MICMAC, in Section 3. Section 4 details the findings of this study. In Section 5, the Managerial and Research Implications of the research are described. Lastly, Section 6 presents the conclusion, including the paper's limitations and future scope.

2. Literature Review

The applications of I4.0 technologies in the digital AFSC have attracted interest due to their ability to transform agricultural practices, increase productivity, and improve food security. Nonetheless, several obstacles to large-scale implementation exist, including technological, organizational, financial, and regulatory ones, which have been discussed in prior literature. This literature review highlights the key obstacles to implementing I4.0 technologies in AFSC.

2.1 Overview of I4.0 in the Agri-Food Supply Chain

The “Fourth Industrial Revolution” involves using devices like computers and sensors connecting to the Internet to automatically share information without human input (Miranda et al., 2019). The IoT, cloud computing, and Cyber-Physical Systems (CPS) are examples of what are commonly referred to as “smart” technology (Nara et al., 2021). These innovative technologies can monitor physical processes, create digital versions of real-world objects, and allow for decisions to be made without a central authority. In farming, they help improve farm operations by coordinating activities within and between farms and organizations. This leads to better productivity and easier delivery of products to customers. Overall, I4.0 aims to make processes more efficient and effective by leveraging advanced technologies to connect people and machines in innovative ways.

Adoption of I4.0 technology has led to the birth of concepts such as “Smart Agriculture,” “Digital Farming,” and “Agriculture 4.0” (Streitz and Konomi, 2025). These terms refer to the interconnectedness of farming operations, both internally and externally (Wolfert et al., 2017; Zhao et al., 2019). This new advancement allows agricultural production stakeholders (farmers, suppliers, distributors, researchers, and consumers) to have access to digital data. The interconnectedness of these stakeholders enables them to communicate electronically regarding their businesses, which allows for real-time decision-making and enhanced cooperation throughout the value chain (Lezoche et al., 2020). For instance, farmers will have immediate access to soil health data, market price data, and weather forecasting data that they can use to assist them in making educated decisions about insect control, planting, irrigating, and harvesting, among other things. Furthermore, ongoing crop and animal monitoring is achieved through IoT sensors, which maximize output and resource management (Babu et al., 2026). The ability to communicate electronically and transfer data streamlines various agricultural operations. Modern technologies such as automated drones for crop monitoring, robots for harvesting, and AI-enabled analytics for predicting yields play crucial roles in reducing labour costs and minimizing waste (Belaud et al., 2019). Integrating internet-based data management solutions improves operational effectiveness and stimulates agricultural innovation, opening the door for sustainable farming methods (Mhlanga and Ndhlovu, 2023). Adopting these tools makes the entire SC more accessible. It responds to the increasing demand from consumers who want to know more about how their food is produced and its source, which has grown among customers. Digital systems provide them with transparency, therefore, enabling them to guarantee the quality and safety of agricultural products and, therefore, create consumer confidence and trust towards producers (Duan et al., 2024).

To conclude, I4.0 technologies in AFSC are not only a matter of technological enhancements but also a comprehensive strategy that will unite productivity, sustainability, and transparency, and can eventually transform the future of farming in the generations ahead (Pandey et al., 2025; Patidar et al., 2018).

2.2 Identification of Barriers to I4.0 Adoption in the Agri-Food Supply Chain

Applied to the agricultural sector, I4.0 technologies will be capable of transforming the AFSC into a more efficient system of production, but a variety of serious barriers will require their possible solutions to make the technologies fully effective for industry participants. The following is a list of the primary organizational, financial, technical, and other legal hurdles that impede the widespread integration of I4.0 technologies in the AFSC.

2.2.1 Technological Barriers

In the digital AFSC, data security and confidentiality are major issues. To maximize inventory management, crop monitoring, and product traceability, AFSC depends on data collected from IoT devices, sensors, and blockchain systems (da Silveira et al., 2025). However, handling sensitive information, such as production data, distribution patterns, and consumer details, raises vulnerabilities. Studies by Alahe et al. (2024) and Sharma et al. (2024) emphasize that cyberattacks, data breaches, and unauthorized access to proprietary agricultural data can undermine consumer trust and food safety. According to Maraveas et al. (2024), security breaches can lead to the mismanagement of food safety protocols and financial losses, emphasizing the need for robust cybersecurity strategies and data encryption technologies.

Eco-innovation is necessary for promoting sustainable agri-food businesses. The lack of eco-friendly innovations, such as resource-efficient farming practices, renewable energy integration, and sustainable packaging, poses a significant barrier to environmental goals. According to Islam et al. (2022), many agri-food firms are reluctant to use “green” technologies because they perceive the initial cost of these technologies as being prohibitively expensive, and they are unsure of the potential long-term benefit of implementing them. Additionally, Bhatia and Kumar (2022) state that sustainable technology integration is

frequently hindered by a lack of cooperation between SC participants, ranging from farmers to manufacturers.

In rural areas and developing regions, the lack of essential technology infrastructure remains an important challenge to adopting advanced I4.0 technologies in agriculture. High-speed internet, reliable power supply, and access to digital tools are often insufficient. Rural communities may face significant challenges in adopting IoT, blockchain, and AI technologies due to poor broadband connectivity and unstable energy supply (Dibbern et al., 2024). Similarly, inadequate infrastructure restricts farmers' ability to collect and transmit real-time data, limiting the effective use of big data for decision-making (Tantalaki et al., 2019).

2.2.2 Organizational and Human Resource Barriers

Apart from technical aspects, organizational and human resource constraints also pose significant hurdles. One major barrier is the lack of training and digital skills among agricultural workers, which creates resistance to adopting advanced technologies (Sinha and Dhanalakshmi, 2022). For example, deploying sophisticated tools like big data analytics or automated systems requires specialized workforce capabilities that are often scarce in the agricultural sector. Training traditional workers to operate these digital tools significantly increases operational and training costs, creating an economic and human-resource paradox for smaller firms (Bhatia and Kumar, 2022). Consequently, without adequate skill development and change management, these human resource constraints directly counteract organizational sustainability and technology adoption efforts (Miranda et al., 2019).

The widespread adoption of IoT devices in farming requires continuous monitoring of crops, soil, and machinery, which demands significant administrative and managerial oversight from the organization (Abbasi et al., 2022; Kumar et al., 2022; Miranda et al., 2019). However, integrating these connected devices often creates organizational overload, particularly in regions lacking digital awareness and leadership support. AFSC typically involves simultaneous activities across multiple departments, creating severe challenges in workforce coordination and data management capacity. Such operational loads often lead to delays in decision-making, administrative failures, and flaws in strategic reasoning, ultimately reducing the overall efficiency of the SC (Chaudhari et al., 2024). The AFSC is a complex system comprising several actors, processes, and geographic locations. Such complexity also complicates the implementation and subsequent delivery of I4.0 technologies that involve coordinating and integrating different systems (Pakseresht et al., 2023). Conventional SCs tend to be highly fragmented, with a lack of transparency among stakeholders. The implementation of digital technologies, such as IoT and AI, in networks can lead to high interconnectedness, which, although theoretically beneficial, can lead to operational inefficiencies in practice unless managed properly.

2.2.3 Financial and Economic Barriers

I4.0 technologies are costly to adopt, both in terms of initial investments in hardware, software, and infrastructure. Ada (2022) indicated that the long-term benefits of such technologies were quite obvious, whereas the preliminary costs of small to medium-sized agri-food businesses may be quite prohibitive. As an illustration, the costs of implementing IoT devices, AI, or robotics can exceed the financial resources of smallholder farmers, and rural agribusinesses cannot afford them. They can barely secure financing or government subsidies (Abbasi et al., 2022). Creative financing options, like the use of public-private partnerships or even customized loan schemes, should enable them to reduce this load and make adopting technology more affordable.

The uncertainty about the return on investment (ROI) may inhibit agri-food businesses from making the required financial investments (Belaud et al., 2019). The effects of I4.0 technology in agriculture do not

always have a clearer or immediate effect than those that happen in manufacturing sectors when one tries to quantify the advantages of automation and digitalization. Uncertainty in achieving a satisfactory ROI, particularly regarding productivity gains, environmental performance, and SC efficiency, may make stakeholders reluctant to commit to the substantial investments required for I4.0 deployment (Junaid et al., 2024). To ease these fears, organizations can conduct pilot projects to gauge potential benefits and collect data to demonstrate tangible ROI.

Inaccessibility to financial resources is a major setback to most stakeholders in the agri-food sector. Rural agribusinesses or smallholders are usually not in a position to take out loans or secure investments to modernize their technology and processes (Akram et al., 2024; Panetto et al., 2020). The perception of foundational risks and uncertainties may prevent financial institutions from investing in agricultural innovations. The key to overcoming this problem is establishing more robust connections between the agricultural community and banks and building novel methods of financing that would address the needs of the farm industry. This can be government projects or grants, whereby agri-tech companies will team up with conventional lenders to develop potential funding.

2.2.4 Policy and Regulatory Barriers

The digital agriculture barriers may not be adequately addressed by existing regulatory frameworks, as I4.0 technologies have been thoroughly integrated into agriculture. To keep abreast of technological changes, policymakers must develop dynamic policies that promote security, environmental preservation, and data privacy. The existing rules can be a barrier to innovation; they impose rigid constraints that do not account for the specifics of modern agricultural work.

One major concern is data ownership and privacy due to the volume of data collected and used by I4.0 technology. The stakeholders might not be confident that someone owns the data they receive on their farms, and how it can be utilized. This uncertainty can become an obstacle to collaboration and data sharing, which are key to achieving the full potential of digital agriculture. To win the confidence of stakeholders, policymakers should devise clear regulations and protocols that address information possession, privacy rights, and the ethical use of agricultural information (da Silveira et al., 2025; Yang et al., 2024). Governments can also provide incentives to stimulate the use of I4.0 technologies in agriculture by using incentive schemes to offset the initial technological investment (i.e., tax exemption, grants, etc.) (Akram et al., 2024). Through financial incentives, governments can alleviate certain economic challenges related to technology adoption, making it easier to implement advanced solutions for farmers and agribusinesses (Zhao et al., 2019; Zhao et al., 2024c). Besides, nations can create innovation centers that foster collaboration between technology developers and agriculturalists, as well as an environment in which both experimentation and development can occur.

To sum up, the I4.0 implementation in agriculture faces many obstacles, but targeted activities in technology integration, data management, human resource development, finance, and policy design can help create a more resilient, efficient, and sustainable agricultural industry. The AFSC can leverage the transformative potential of I4.0 to drive future growth and sustainability. **Table 1** summarizes the discussed barriers.

2.3 Research Gap

The literature above suggests that numerous studies have focused on identifying the barriers to the adoption of I4.0 technology in the AFSC. Nevertheless, even with sufficient literature, many gaps remain. The lack of universal communication protocols and standard data formats impedes seamless integration across the AFSC. The application of I4.0 solutions should be customized to serve the various stakeholders, such as smallholder farmers and large agribusinesses. Also, scant research has been conducted on data governance

models that address the ownership, control, and sharing benefits of agricultural data. The reusability and recyclability of I4.0 technologies, which are also environmental aspects, should be investigated further.

Last but not least, the socio-economic consequences of I4.0 adoption still require a more thorough focus on its future implications for agricultural productivity and the rural population. Addressing these gaps will help advance knowledge and enhance the development of sustainable strategies for the digital transformation of agriculture. Therefore, this study contributes to the field by analyzing these barriers using the Matrix of Cross-Impacts-Multiplication Applied to a Classification (MICMAC) with Interpretive Structural Modeling (ISM). This method strengthens the conclusions by systematically analyzing obstacles, ranking them by severity, and classifying them as dependent, independent, linkage, or autonomous variables. The research provides practical insights to minimize risks, increase stakeholder cooperation, and achieve sustainability, which will help establish a powerful and effective digital AFSC.

2.4 Research Framework

Here, as depicted in **Figure 1**, we propose adopting a conceptual framework to explore the barriers of I4.0 technology adoption in the digital AFSC. This framework offers a robust foundation for identifying, evaluating, and categorizing the barriers to I4.0 adoption. It is grounded in the existing literature and justified by professional judgment, making it relevant and comprehensive. The steps included in the framework are the following:

- 1) The first is to conduct a comprehensive literature review using sources such as Scopus, ScienceDirect, Web of Science, and Google Scholar. The review helps determine the barriers to the adoption of I4.0 technologies in digital AFSC. Having been identified, such barriers were listed and assessed by specialists in the agri-food and I4.0 technologies field. Experts helped create the final list of relevant, comprehensive barriers.
- 2) The interaction among the barriers was analyzed using the ISM after identifying them. This method entails several stages to determine precisely whether all barriers affect other parties. A questionnaire was developed and sent to a group of specialists to capture information regarding these interrelationships. These responses help develop a Structural Self-Interaction Matrix (SSIM), which defines direct connections between barriers. Based on the SSIM, a Reachability Matrix was created that determines direct and indirect relationships. The result of the ISM process is the categorization of the barriers into hierarchical levels with an emphasis on their relative significance.
- 3) The Fuzzy-MICMAC method was used to evaluate driving and dependence power for barriers, thereby creating classifications of “autonomous”, “dependent”, “linkage”, and “independent” based on both their influence and their relationships with other barriers. By using fuzzy logic, the methodology accounts for uncertainties in expert judgments, strengthening the analysis. In this step, a Fuzzy Reachability Matrix was constructed to refine the relationships between barriers.
- 4) This was followed by defining a fuzzy hierarchy that categorizes the barriers according to their influence and dependence in the adoption process.
- 5) The analysis’s findings can provide managers and leaders with crucial information in the digital AFSC. Managers can prioritize the most important issues and focus on resolving those with the greatest driving and dependency power by recognizing and understanding the connections among the obstacles. Organizational preparedness for I4.0 technology adoption will increase as a result. This research highlights the implications of the successful use of I4.0 technologies in the AFSC and provides recommendations for further studies.

3. Research Methodology

In this section, the methods used to model the barriers to adopting I4.0 technologies in the digital AFSC are described. The introduction of ISM mapping barriers and the generation of the initial and end reachability matrices are the primary subjects of the first sub-section, which is accompanied by the generation of the ISM model. The second sub-section uses Fuzzy-MICMAC analysis, which maps the barriers to create fuzzy reachability matrices and plots a driving-dependency diagram to examine the interdependencies of barriers.

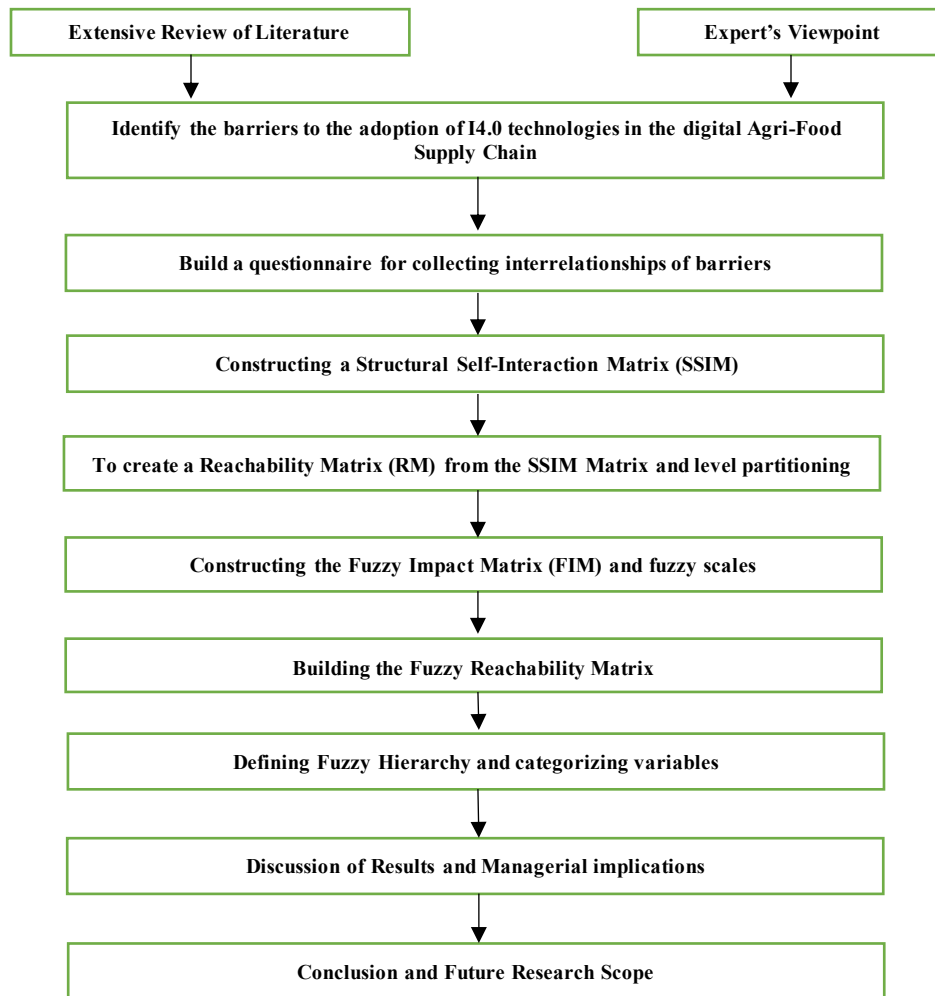


Figure 1. Research framework and work process.

3.1 ISM Technique

Some barriers are independent, and those which depend on another barrier or on a number of barriers. As an example, “Lack of eco-innovation” seems to be influenced by “Lack of technological infrastructure”, whereas it seems that “High initial cost” and “ROI uncertainty” do not correlate. Nevertheless, it turned out, as it became obvious after speaking with industry professionals and thoroughly analysing the literature, that all the barriers are interrelated with most of the others. These links are thoroughly examined in this study. The following symbols are used to illustrate potential permutations of interactions between barriers:

V = Barrier 'j' is influenced by barrier 'i'.
 A = Barrier 'i' is influenced by barrier 'j'.
 X = Barriers 'i' and 'j' influence each other.
 O = Barriers 'i' and 'j' are unaffected.
 i = Row element (the factor being considered as influencing others).
 j = Column element (the factor being influenced).

Each barrier is assigned a sequence number, and the mapping of these relationships is presented below:

T01: Security and privacy.
 T02: Lack of eco-innovation.
 T03: Lack of technological infrastructure.
 T04: Big data management.
 T05: Technological immaturity.
 T06: Energy-intensive technology.
 OP01: High energy consumption.
 OP02: Congestion and overload issues in IoT (Internet of Things).
 OP03: Lack of trust among stakeholders.
 OP04: Complex supply chain network.
 OR01: Lack of training programs.
 OR02: IoT-based infrastructure.
 OR03: Resistance to change.
 OR04: Lack of top management support.
 S01: Lack of government regulation.
 S02: High initial cost and ROI uncertainty.
 S03: Short-term focus on sustainability goals.
 S04: Cultural resistance.

Table 1. The barriers to adopting I4.0 technologies in the digital agri-food supply chain.

Category	Barriers	Definition	References
Technical	Security and privacy (T01).	The AFSC deals with sensitive data of production, distribution and consumer information. The vulnerabilities may result in data breaches, which undermine consumer trust and endanger food safety.	Mehmood et al. (2021), Yadav et al. (2020).
	Lack of eco-innovation (T02).	Sustainability-related innovations, like environmentally friendly packaging or resource-saving agricultural methods, are not always available. This complicates efforts to alleviate the adverse environmental impact of agri-food systems.	Kumar et al. (2021).
	Lack of technology infrastructure (T03).	Advanced technologies like IoT and blockchain might not be readily accepted in many regions, particularly in rural ones, because they require digital infrastructure (e.g., broadband internet) that many regions do not yet have.	Gedam et al. (2021), Kamble et al. (2019).
	Big data management (T04).	The massive volumes of data generated by IoT devices in the agricultural sector (e.g., agricultural sensors, weather data) present challenges in integrating, analyzing, and taking meaningful action, which is central to maximizing sustainability outcomes.	Haddout and Kurniawan (2026), Tseng et al. (2019).
	Technological immaturity (T05).	Numerous digital solutions are at an initial development stage. The result of this immaturity is reliability and could demotivate the stakeholders to be fully dedicated to such technologies.	Batra et al. (2025), Kamble et al. (2020), Liu et al. (2021).
	Energy-intensive technology (T06).	Advanced technologies, particularly those requiring significant computational power (like AI), can lead to high energy consumption, counteracting sustainability goals.	Yadav et al. (2020).
Operational	High energy consumption (OP01).	Traditional agri-food operations are often energy-intensive, and integrating digital technologies can exacerbate this, impacting overall sustainability.	Yadav et al. (2020).

Table 1 continued...

	Congestion and overload issue of IoT (OP02).	The proliferation of connected devices can overwhelm existing networks, leading to inefficiencies and potential failures in monitoring and managing supply chain processes.	Kamble et al. (2020).
	Lack of trust among stakeholders (OP03).	The stakeholders (farmers, suppliers, and retailers) may be hesitant to open up because of the fear of confidentiality and competitions, which complicates the cooperation required in adopting sustainable practices.	Kamble et al. (2019), Kamble et al. (2020).
	Complex supply chain network (OP04).	The AFSC brings together multiple market participants and processes, creating complexity that can obscure transparency and accountability, making it difficult to implement sustainability initiatives.	Dai and Lu (2026), Mehmood et al. (2021).
Organizational	Lack of training programs (OR01).	Many organizations fail to adequately train their staff on new and sustainable technologies, resulting in underutilization of digital tools and missed opportunities for improvement.	Gedam et al. (2021).
	IoT-based infrastructure (OR02).	Transitioning to IoT-based systems requires significant changes in existing infrastructure. Many organizations struggle with integration, leading to inefficiencies.	Kazancoglu et al. (2021).
	Resistance to change (OR03).	Organizational resistance to change can impede the implementation of new practices and technology essential for enhancing sustainability.	Kumar et al. (2021).
	Lack of top management support (OR04).	Without strong leadership commitment, initiatives aimed at sustainability and digital transformation may lack the resources and attention needed to sustain progress.	Kamble et al. (2020).
Strategic	Lack of government regulation (S01).	A lack of or inconsistency of sustainability rules produces an ambiguous situation in front of the companies and requires them to invest at a greater difficulty in long-term sustainable projects.	Tseng et al. (2019).
	High initial cost and ROI uncertainty (S02).	The initial investment required for digital technologies can be disheartening, particularly when the payback (ROI) remains uncertain, discouraging stakeholders from engaging in sustainability efforts.	Parra-López and Carmona-Torres (2026), Yadav et al. (2020).
	Short-term focus on sustainability goals (S03).	Most organizations are concerned with immediate monetary reward at the expense of long-term sustainability, resulting in short-term practices that are economically viable but harmful to the environment.	Kazancoglu et al. (2021).
	Cultural resistance (S04).	Deep-rooted cultural attitudes may prioritize traditional methods over innovative, sustainable practices, making it difficult to shift towards more sustainable operations.	Lara et al. (2023).

3.1.1 Creation of the Structural Self-Interaction Matrix (SSIM)

The ISM method is satisfactory for the type of structured model discussed in this study, as it relies on expert opinions. In this study, the opinions of 20 experts were collected, 15 of whom have experience in the agriculture industry, while 5 are academic professionals (Table 2). Each participant has extensive expertise and experience in this field, particularly an understanding of barriers and how one barrier depends on another, making them well-qualified to explore and examine the relationships among various barriers—specifically, their interdependence.

Table 2. Profile of experts.

Sr. No.	Category	Sub-category	No. of experts	Working experiences
1.	Agriculture Industry	Farmers & Producers	5	10-12
2.		Supply Chain Managers	5	10-15
3.		Agribusiness Executives	5	10-15
4.	Academic Professionals	Operations Research	2	7-8
5.		Agricultural Economists	2	5-6
6.		Supply Chain Theorists	1	6-7

The symbols ‘i’ and ‘j’ indicate the dependencies between the barriers, and their interactions are depicted by direction. An 18×18 SSIM is created based on these contextual linkages, and the filled values are displayed in Table 3. This table was filled with expert judgments, and the symbols in the matrix were assigned based on direct connections between the barriers. To ensure methodological reliability, the

relationships among the barriers were established through consensus-based discussions among the experts. When differences in opinion appeared, the majority rule was applied to reach a final decision. Furthermore, logical consistency was maintained by verifying transitivity while developing the reachability matrix.

3.1.2 An Explanation of SSIM

The ‘O’ symbol appears far more frequently than the other symbols, according to a brief observation. This means that although individual obstacles to the problem have been studied in isolation, no attempt has been made to examine the collective barriers. There is therefore still no clear understanding of how some barriers within the same group are interconnected. However, experts have identified connections between certain barriers represented by the ‘V’, ‘A’, and ‘X’ symbols. Nevertheless, a more thorough investigation is needed to establish the relationships among all the barriers.

Table 3. Structural self-interaction matrix.

Variable	T01	T02	T03	T04	T05	T06	OP01	OP02	OP03	OP04	OR01	OR02	OR03	OR04	S01	S02	S03	S04
T01		X	V	A	X	V	X	V	A	X	V	O	A	A	O	A	X	V
T02			X	A	V	X	A	X	V	X	O	A	V	V	A	X	A	A
T03				A	X	V	X	V	X	V	X	A	V	O	X	V	A	X
T04					A	X	V	A	X	A	A	X	A	X	O	A	X	V
T05						V	O	X	A	X	X	V	X	A	A	X	V	X
T06							X	V	O	X	V	A	V	X	A	X	X	V
OP01								O	A	X	V	X	O	A	A	V	X	X
OP02									X	V	A	V	X	O	O	A	V	A
OP03										A	O	X	V	O	V	O	A	X
OP04											A	A	A	V	O	V	X	A
OR01												O	V	V	A	X	O	A
OR02													A	O	V	A	X	O
OR03														O	A	X	V	V
OR04															O	A	X	A
S01																O	A	A
S02																	X	O
S03																		A
S04																		

Table 4. Initial reachability matrix.

Variable	T01	T02	T03	T04	T05	T06	OP01	OP02	OP03	OP04	OR01	OR02	OR03	OR04	S01	S02	S03	S04
T01	1	1	1	0	1	1	1	1	0	1	1	0	0	0	0	0	1	1
T02	1	1	1	0	1	1	0	1	1	1	0	0	1	1	0	1	0	0
T03	0	1	1	0	1	1	1	1	1	1	1	0	1	0	1	1	0	1
T04	1	1	1	1	0	1	1	0	1	0	0	1	0	1	0	0	1	1
T05	1	0	1	1	1	1	0	1	0	1	1	1	1	0	0	1	1	1
T06	0	1	0	1	0	1	1	1	0	1	1	0	1	1	0	1	1	1
OP01	1	1	1	0	0	1	1	0	0	1	1	1	0	0	0	1	1	1
OP02	0	1	0	1	1	0	0	1	1	1	0	1	1	0	0	0	1	0
OP03	1	0	1	1	1	0	1	1	1	0	0	1	1	0	1	0	0	1
OP04	1	1	0	1	1	1	1	0	1	1	0	0	0	1	0	1	1	0
OR01	0	0	1	1	1	0	0	1	0	1	1	0	1	1	0	1	0	0
OR02	0	1	1	1	0	1	1	0	1	1	0	1	0	0	1	0	1	0
OR03	1	0	0	1	1	0	0	1	0	1	0	1	1	0	0	1	1	1
OR04	1	0	0	1	1	1	1	0	0	0	0	0	1	1	0	0	1	0
S01	0	1	1	0	1	1	1	0	0	0	1	0	1	0	1	0	0	0
S02	1	1	0	1	1	1	0	1	0	0	1	1	1	1	0	1	1	0
S03	1	1	1	1	0	1	1	0	1	1	1	1	0	1	1	1	1	0
S04	0	1	1	0	1	0	1	1	1	1	1	0	0	1	1	0	1	1

3.1.3 The Reachability Matrix's Creation (RM)

The reachability matrix is created after the SSIM matrix. This matrix is binary, with '0' denoting no influence and '1' denoting the influence of barrier (i) on barrier (j), as shown in **Table 4**. It encompasses both transitive links and direct and indirect connections between barriers. The upper-diagonal section of the reachability matrix contains scores corresponding to the symbols in the SSIM matrix. The fundamental procedures of the ISM approach are used to complete the lower diagonal section, accounting for both forward and reverse relationships. The entire matrix is filled in this manner.

3.1.4 Level Classification of Barriers

Using the created reachability matrix, the next step is to group the barriers into different levels. In this process, the antecedent and reachability sets will be defined as shown in **Table 5**. The antecedent set consists of the barrier under analysis and any other barriers it may affect (the reachability set). Both of these are the same barrier, and any other barriers it can reach. The intersection of two sets contains elements that are in both sets. The next step in defining a level is to determine the intersection of the antecedent set and the reachability set, and to eliminate the values in the reachability set that result from that intersection. This will be done recursively until the levels are established.

Table 5. Level partition on reachability matrix.

Variable	Reachability set	Antecedent set	Intersection set	Level
T01	T01, T02, T03, T05, T06, OP01, OP02, OP04, OR01, S03, S04.	T01, T02, T04, T05, OP01, OP03, OP04, OR03, OR04, S02, S03.	T01, T02, T05, OP01, OP04, S03.	5
T02	T01, T02, T03, T05, T06, OP02, OP03, OP04, OR03, OR04, S02.	T01, T02, T03, T04, T06, OP01, OP02, OP04, OR02, S01, S02, S03, S04.	T01, T02, T03, T06, OP02, OP04, S02.	3
T03	T02, T03, T05, T06, OP01, OP02, OP03, OP04, OR01, OR03, S01, S02, S04.	T01, T02, T03, T04, T05, OP01, OP03, OR01, OR02, S01, S03, S04.	T02, T03, T05, OP01, OP03, S03, S04.	5
T04	T01, T02, T03, T05, T06, OP01, OP03, OR02, OR04, S03, S04.	T04, T05, T06, OP02, OP03, OP04, OR01, OR02, OR03, OR04, S02, S03.	T05, T06, OP03, OR02, OR04, S03.	3
T05	T01, T03, T04, T05, T06, OP02, OP04, OR01, OR02, OR03, S02, S03, S04.	T01, T02, T03, T05, OP02, OP03, OP04, OR01, OR03, OR04, S01, S02, S04.	T01, T03, T05, OP02, OP04, OR01, OR03, S02, S04.	5
T06	T02, T04, T06, OP01, OP02, OP04, OR01, OR03, OR04, S02, S03, S04.	T01, T02, T03, T04, T05, T06, OP01, OP04, OR02, OR04, S01, S02, S03.	T02, T04, T06, OP01, OP04, OR04, S02, S03.	5
OP01	T01, T02, T03, T06, OP01, OP04, OR01, OR02, S02, S03, S04.	T01, T03, T04, T06, OP01, OP03, OP04, OR02, OR04, S01, S03, S04.	T01, T03, T06, OP01, OP04, OR02, S03, S04.	5
OP02	T02, T04, T05, OP02, OP03, OP04, OR02, OR03, S03.	T01, T02, T03, T05, T06, OP02, OP03, OR01, OR03, S02, S04.	T02, T05, OP02, OP03, OR03.	3
OP03	T01, T03, T04, T05, OP01, OP02, OP03, OR02, OR03, S01, S04.	T02, T03, T04, OP02, OP03, OP04, OR02, S03, S04.	T03, T04, OP02, OP03, OR02, S04.	4
OP04	T01, T02, T04, T05, T06, OP01, OP03, OP04, OR04, S02, S03.	T01, T02, T03, T05, T06, OP01, OP02, OP04, OR01, OR02, OR03, S03, S04.	T01, T02, T05, T06, OP01, OP04, S03.	2
OR01	T03, T04, T05, OP02, OP04, OR01, OR03, OR04, S02.	T01, T03, T05, T06, OP01, OR01, S01, S02, S03, S04.	T05, OR01, S02.	5
OR02	T02, T03, T04, T06, OP01, OP03, OP04, OR02, S01, S03.	T04, T05, OP01, OP02, OP03, OR02, OR03, S02, S03.	T04, OP01, OP03, OR02, S03.	3
OR03	T01, T04, T05, OP02, OP04, OR02, OR03, S02, S03, S04.	T02, T03, T05, T06, OP02, OP03, OR01, OR03, S01, S02.	T05, OP02, OR03, S02.	4
OR04	T01, T04, T05, T06, OP01, OR04, S03.	T02, T04, T06, OP04, OR01, OR04, S02, S03, S04.	T04, T06, OR04, S03.	1
S01	T02, T03, T05, T06, OP01, OR01, OR03, S01.	T03, OP03, OR02, S01, S03, S04.	T03, S01.	5
S02	T01, T02, T04, T05, T06, OP02, OR01, OR02, OR03, OR04, S02, S03.	T02, T03, T05, T06, OP01, OP04, OR01, OR03, S02, S03.	T02, T05, T06, OR01, OR03, S02, S03.	5
S03	T01, T02, T03, T04, T06, OP01, OP03, OP04, OR01, OR02, OR04, S01, S02, S03.	T01, T04, T05, T06, OP01, OP02, OP04, OR02, OR03, OR04, S02, S03, S04.	T01, T04, T06, OP01, OP04, OR02, OR04, S02, S03.	5
S04	T02, T03, T05, OP01, OP02, OP03, OP04, OR01, OR04, S01, S03, S04.	T01, T03, T04, T05, T06, OP01, OP03, OR03, S04.	T03, T05, OP01, OP03, S04.	5

3.1.5 Framing of ISM-Based Model (Barriers Hierarchy)

Figure 2 shows the structural model created using the information gathered and illustrated in Table 1. By removing transitivity and using the ISM methodology, this model was created.

3.1.6 Results of the ISM-Based Framework

Five levels make up the ISM-based framework, which is separated into three criticality-based categories: “most crucial,” “reasonably crucial,” and “least crucial.” The most significant group includes level 5 barriers. Because they affect other barriers, these barriers are considered crucial. T01, T03, T05, T06, OP01, OR01, S01, S02, S03, and S04 are the barriers in this category. Reducing these barriers can potentially help with the other obstacles based on domino effect. Level 2, Level 3, and Level 4 barriers fall into the moderately crucial category. The most important hurdles affect these barriers, which, in turn, influence the least important barriers. The barriers in this category are OP04, T02, T04, OP02, OR02, OP03, and OR03. Finally, the least crucial category consists of Level 1 barriers, with OR04 as the only barrier. Other barriers drive this barrier, making it less critical than the others in the hierarchy.

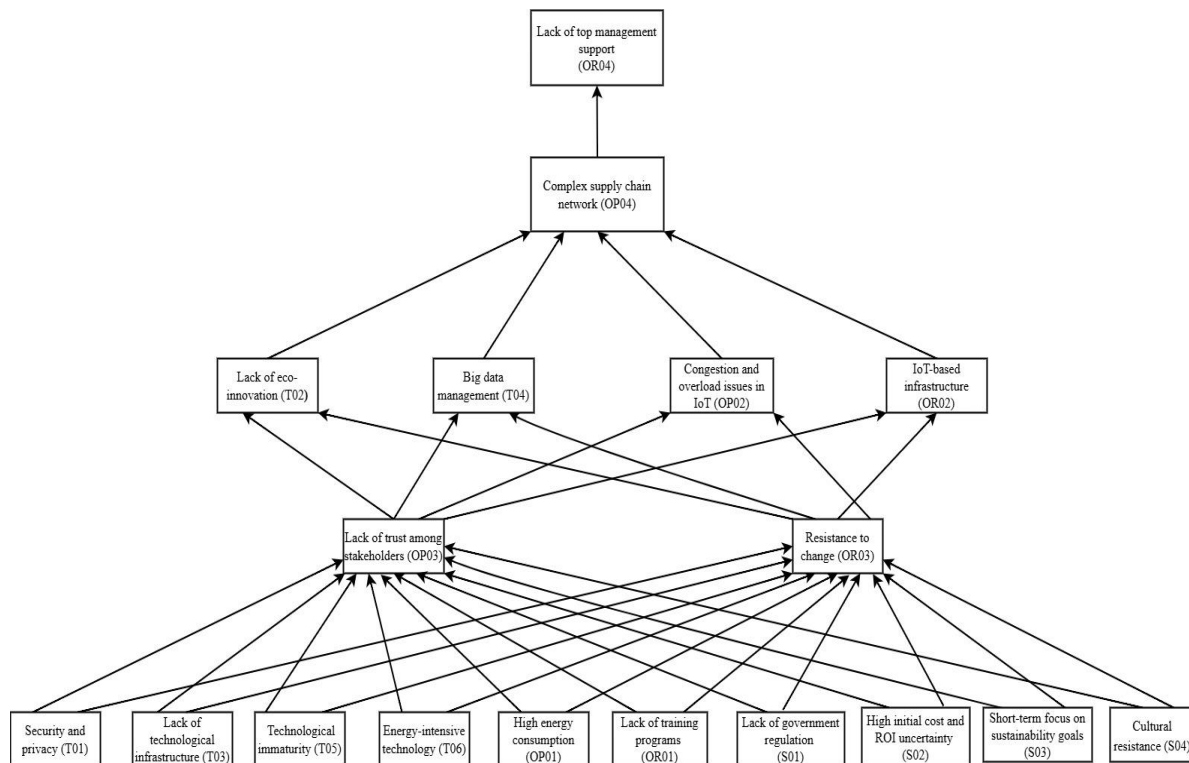


Figure 2. ISM hierarchical model for I4.0 barriers to adoption.

3.2 Fuzzy-MICMAC Analysis

At the final stage of this analysis, Fuzzy-MICMAC was applied to determine the categories of the elements based on their relationships of influence and dependency. There are four categories into which the barriers can fall: autonomous, dependent, linkage, and independent. Dependent-driven barriers are, in most cases, influenced by external sources, whereas driving-driven barriers have a large influence on the entire system (Chuaphun and Samanchuen, 2024). The RM created during the ISM phase provides the data for this

procedure. Linguistic phrases are translated into numerical values by experts to evaluate the impact of these elements. Fuzzy logic is used to account for the imprecision and uncertainty in these interactions, making the analysis more adaptable and practical (Chuaphun and Samanchuen, 2024; Zhao et al., 2025). The following linguistic terms were mapped to numerical values:

- No Influence: 0
- Very Weak Influence: 0.133
- Weak Influence: 0.333
- Medium Influence: 0.5
- Strong Influence: 0.7
- Very Strong Influence: 0.867
- Complete Influence: 1

After these values are allocated, Fuzzy-MICMAC calculations are performed to produce the stabilized matrix **Table 6**. This matrix helps identify the relationship and classification of the barriers. This in-depth analysis provides insight into how the system's components work and how more critical strategic planning and decision-making can be conducted.

Table 6. Fuzzy stabilized matrix (FSM).

Variable	T01	T02	T03	T04	T05	T06	OP01	OP02	OP03	OP04	OR01	OR02	OR03	OR04	S01	S02	S03	S04	DP
T01	0	0.5	0.7	0	0.333	0.7	0.333	0.7	0	0.333	0.7	0	0	0	0	0	0.7	0.7	5.699
T02	0.5	0	0.333	0	0.7	0.333	0	0.5	0.7	0.7	0	0	0.7	0.7	0	0.333	0	0	5.499
T03	0	0.333	0	0	0.7	0.333	0.5	0.7	0.333	0.7	0.333	0	0.5	0	0.333	0.7	0	0.333	5.798
T04	0.5	0.5	0.5	0	0	0.7	0.7	0	0.333	0	0	0.7	0	0.5	0	0	0.333	0.7	5.466
T05	0.333	0	0.7	0.5	0	0.5	0	0.333	0	0.5	0.333	0.7	0.5	0	0	0.333	0.7	0.5	5.932
T06	0	0.333	0	0.7	0	0	0.7	0.5	0	0.5	0.7	0	0.7	0.333	0	0.333	0.5	0.7	5.999
OP01	0.33	0.5	0.5	0	0	0.7	0	0	0	0.5	0.7	0.5	0	0	0	0.5	0.7	0.333	5.263
OP02	0	0.5	0	0.5	0.333	0	0	0	0.333	0.7	0	0.7	0.5	0	0	0	0.7	0	4.266
OP03	0.5	0	0.333	0.333	0.7	0	0.7	0.333	0	0	0	0.5	0.7	0	0.7	0	0	0.5	5.299
OP04	0.333	0.7	0	0.7	0.5	0.5	0.5	0	0.7	0	0	0	0	0.7	0	0.7	0.333	0	5.666
OR01	0	0	0.333	0.5	0.333	0	0	0.5	0	0.5	0	0	0.333	0.5	0	0.55	0	0	3.549
OR02	0	0.5	0.7	0.7	0	0.5	0.5	0	0.5	0.5	0	0	0	0	0.7	0	0.333	0	4.933
OR03	0.5	0	0	0.5	0.5	0	0	0.5	0	0.333	0	0.7	0	0	0	0.5	0.7	0.7	4.933
OR04	0.5	0	0	0.5	0.7	0.333	0.5	0	0	0	0	0	0	0	0	0	0.7	0	3.233
S01	0	0.5	0.333	0	0.5	0.5	0.5	0	0	0	0.333	0	0.5	0	0	0	0	0	3.166
S02	0.5	0.333	0	0.5	0.333	0.333	0	0.5	0	0	0.5	0.5	0.5	0.5	0	0	0.5	0	4.999
S03	0.7	0.5	0.5	0.333	0	0.5	0.7	0	0.7	0.333	0	0.333	0	0.7	0.5	0.5	0	0	6.299
S04	0	0.7	0.333	0	0.5	0	0.333	0.5	0.5	0.7	0.333	0	0	0.7	0.7	0	0.7	0	5.999
Dependence	4.696	5.899	5.265	5.766	6.132	5.932	5.966	5.066	4.099	6.299	3.932	4.633	4.933	4.633	2.933	4.449	6.899	4.466	-

3.2.1 Insights from Fuzzy-MICMAC Analysis

Each barrier driving and dependence power was computed in decimal form after the Fuzzy-MICMAC analysis. The autonomous, dependent, linkage, and independent cause quadrants were used to divide the barriers into four groups based on these values. These quadrants are shown in **Figure 3** based on their driving and dependency power.

• Autonomous Barriers

Barriers in this category exhibit low driving and low dependence power. These barriers are neither significantly influenced by others nor have a considerable impact on other barriers. The autonomous barriers identified in this study are OR01 and S01.

- **Dependent Barriers**

Dependent barriers have low driving power but high dependence power. They may not have much effect of their own, but other barriers greatly impact them. The dependent barriers in this study are OP02 and OR04.

- **Linkage Barriers**

Due to their high driving power and high reliance power, the linking barriers both impact and are influenced by several systemic aspects. The barriers in this category include T01, T02, T03, T04, T05, T06, OP01, OP04, OR03, OR02, and S03. These barriers play a central role in the system, driving the relationships among them.

- **Independent Barriers**

Barriers in this category exhibit high driving power but low dependence power. These barriers can influence other barriers, but are not significantly affected by other barriers. The independent barriers identified are OP03, S02, and S04.

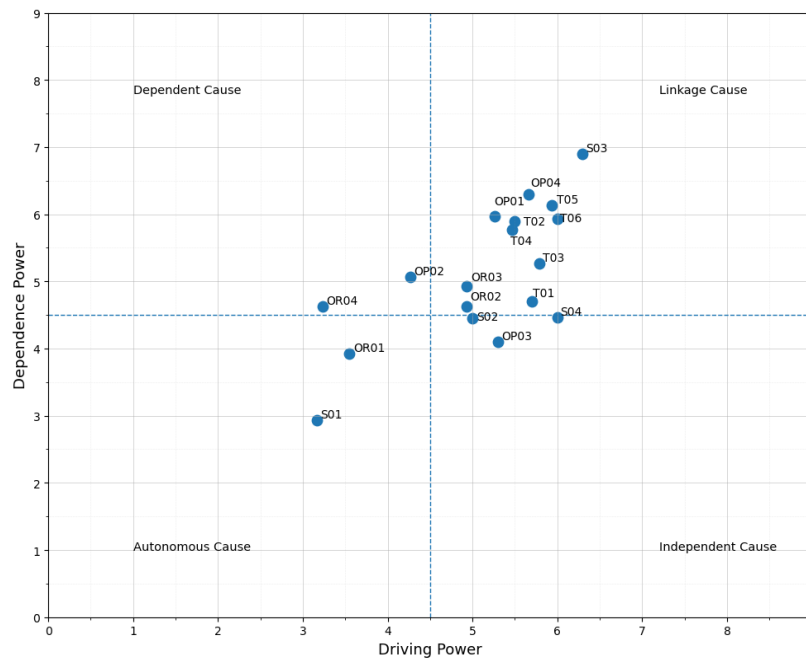


Figure 3. Fuzzy-MICMAC driving-dependence power diagram categorizing barriers into autonomous, dependent, linkage, and independent groups.

4. Results and Discussion

The findings from this research address the three objectives of our study with respect to their applicability for determining how to implement I4.0 technologies to realize sustainability in AFSC. This research builds on ISM and Fuzzy-MICMAC analyses to create a hierarchical model of the identified barriers and their interrelationships, rather than discussing barriers as previous studies have. To fulfil these objectives, we first identified 18 barriers that could impede the implementation of I4.0 in AFSC. Second, we prioritize the barriers by categorizing them and assigning levels. Third, we created models to illustrate the interrelationships and categorizations among these barriers, providing insights into which require critical

attention. This integrated modeling approach therefore strengthens the theoretical understanding of systemic barriers in digital AFSC transformation.

4.1 ISM Result

Our ISM model maps out the interconnections between the identified barriers to adopting I4.0 technologies in the digital AFSC. The practitioners could use this knowledge to design appropriate strategies for successfully implementing I4.0 technologies in the AFSC. The ISM analysis revealed a five-level hierarchical structure illustrating how the identified barriers are interrelated. Level one has only one barrier: “Lack of top management support (OR04)”. Level two of the hierarchy includes “Complex supply chain network (OP04)”, Level three consists of “IoT-based infrastructure (OR02)”, “Congestion and overload issue of IoT (OP02)”, “Lack of eco-innovation (T02)”, and “Big data management (T04)”. Level four of the hierarchy includes “Lack of trust among stakeholders (OP03)” and “Resistance to change (OR03)”. Level five contains “Security and privacy (T01)”, “Lack of technology infrastructure (T03)”, “Technological immaturity (T05)”, “Energy-intensive technology (T06)”, “High energy consumption (OP01)”, “Lack of training programs (OR01)”, “Lack of government regulation (S01)”, “High initial cost and ROI uncertainty (S02)”, “Short-term focus on sustainability goals (S03)”, and “Cultural resistance (S04)”.

The “Security and privacy (T01)”, “Lack of technology infrastructure (T03)”, “Technological immaturity (T05)”, “Energy-intensive technology (T06)”, “High energy consumption (OP01)”, “Lack of training programs (OR01)”, “Lack of government regulation (S01)”, “High initial cost and ROI uncertainty (S02)”, “Short-term focus on sustainability goals (S03)”, and “Cultural resistance (S04)” stood out as the dominant barriers to I4.0 adoption in the digital AFSC as they constitute the base of ISM hierarchy. This finding confirms previous studies that highlight infrastructure and financial uncertainty as the most significant barriers. However, it supplements this by showing how the two aspects structure dominates in the hierarchical context of the structural effect of the two as one. Worth noting is that the “Lack of top management support (OR04)” appears to be the highest level, and finer financial and technological limitations may even influence the manager’s commitment. This contrasts with research that has cited management support as the root barrier of the same.

4.2 Fuzzy-MICMAC Results

The identified barriers were grouped into four distinct groups, namely: autonomous, dependent, independent and linkage.

Autonomous: Low dependence and driving power are two of the characteristics of an autonomous barrier. These barriers are normally not associated with the rest of the system. Two barriers in the autonomous category that would be included in our discussion include “Lack of training programs (OR01)” and “Lack of government regulation (S01)”. With the current trend of digitization and new governance methods, it is not difficult to access training programs and government regulations on implementing I4.0 in the digital AFSC. Nevertheless, there is another barrier that addresses these aspects to overcome them.

Dependent: The barriers in this quadrant highly rely on others and have low driving potential. Their main emphasis is on performance, and they are normally located at the upper levels of the ISM hierarchy. In this respect, the dependent barriers include the “Congestion and overload issue of IoT (OP02)” and the “Lack of top management support (OR04)”. This implies that these barriers are largely consequences of deeper structural issues rather than primary causes. Addressing foundational technological and financial constraints may therefore reduce the intensity of these dependent barriers.

Independent: These barriers have a comparatively strong driving power and extremely little dependence on other barriers. Given that they also underlie another barrier, these barriers need to be addressed with the utmost seriousness.

If these barriers are eliminated, the impact of obstacles at the top and middle levels of the ISM hierarchy will also be reduced automatically. This includes the following in our situation: “High initial cost and ROI uncertainty (S02)”, “Cultural resistance (S04)”, and “Lack of trust among stakeholders (OP03)”.

Linkage: Although these barriers have considerable driving power, they also rely heavily on others. Because of their sensitivity, they are frequently characterized as extremely unstable. In this situation, “High energy consumption (OP01)”, “Complex supply chain network (OP04)”, “IoT-based infrastructure (OR02)”, “Resistance to change (OR03)”, “Short-term focus on sustainability goals (S03)”, “Security and privacy (T01)”, “Lack of eco-innovation (T02)”, “Lack of technology infrastructure (T03)”, “Big data management (T04)”, “Technological immaturity (T05)” and “Energy-intensive technology (T06)”, barriers were found in the set of linkages. Due to their dual nature (high driving and high dependence), these barriers are structurally sensitive and require coordinated policy and managerial interventions rather than isolated corrective actions.

The results align with earlier studies that identified technological, financial, and infrastructural barriers as essential for the adoption of I4.0. This study builds on previous research by using ISM–Fuzzy MICMAC to show how these barriers are organized and how they depend on each other. Previous research has characterized top management support as a driving factor; however, the findings indicate it functions as a dependent barrier. In the AFSC, management’s willingness to adopt I4.0 relies heavily on foundational external factors, including regulatory frameworks, infrastructure readiness, and high initial investment requirements, rather than serving as an independent driver.

5. Managerial and Research Implications

The current study was conducted to assist individuals and organizations within AFSC in developing countries in overcoming major adoption obstacles to I4.0. Using the developed ISM model, AFSC professionals can formulate short, medium, and long-term tactics to adopt I4.0 practices effectively.

From the strategic aspects, agribusiness institutions should prioritize addressing fundamental barriers, including Security and privacy (T01), Lack of technology infrastructure (T03), Technological immaturity (T05), Energy-intensive technology (T06), High energy consumption (OP01), Lack of training programs (OR01), Lack of government regulation (S01), High initial cost and ROI uncertainty (S02), Short-term focus on sustainability goals (S03), and Cultural resistance (S04). For I4.0 to succeed, governments and corporate leaders need to support people in adapting to a changing environment. Right now, the efforts being made need greater understanding during this transition period. Companies need to explore how they can help people understand these technologies. Ultimately, ecosystems need to be developed that allow everyone involved to share ideas, collaborate, and get the education they need to make the most of these new tools.

Additionally, both the government and organizations may offer rewards and incentives to encourage the adoption of these policies. Organizations should also advocate for government support to secure financial assistance, grants, and incentives to develop more sustainable products and promote environmental initiatives. Study findings indicate that organizations must examine employees’ behavior, as it may influence operations, particularly when there is potential fear of transformation. Top leaders may consider the following barriers when planning the intermediate strategy: IoT-based infrastructure (OR02),

Congestion and overload issues of IoT (OP02), Lack of eco-innovation (T02), Big data management (T04), Lack of trust among stakeholders (OP03), and Resistance to change (OR03). To bring I4.0 into operations, organizations need to align both teams and customers. They can organize training programs to roll out I4.0 technologies more smoothly, thereby creating stronger relationships with their customers. When stakeholders are aligned, sustainable I4.0 systems become more effective and efficient.

From a managerial perspective, organizations should also prioritize addressing barriers such as financial investment, technological readiness, and organizational culture, as doing so can reduce other dependent barriers. The presence of linkage barriers further underscores the need for coordinated collaborative strategies. Socially, improving awareness, skills, and stakeholder trust can enhance the adoption of sustainable practices.

6. Conclusion

This research identifies 18 key barriers to I4.0 adoption in the digital AFSC. Many of these barriers were underexplored in the existing literature. Our integrated ISM model reveals a hierarchical structure where fundamental barriers, such as security and privacy, lack of technology infrastructure, technological immaturity, and high initial cost, are the most critical. Managers should primarily focus on high-impact barriers, such as initial investment uncertainty, cultural resistance, and stakeholder trust, as addressing these can reduce related operational barriers. Addressing independent and linkage barriers triggers broader improvements, thereby reducing the overall complexity of implementation barriers.

The results can assist managers in prioritizing barriers and action plans, and allocating resources. Technological infrastructure and financial risk are fundamental problems that can drive improvements across various operations. These suggestions guide policymakers and practitioners in designing specific policies to enhance sustainability in AFSC and facilitate the successful implementation of I4.0. Prioritizing interventions based on their influence and interconnectedness can have a domino effect on the system. Organizations will be better positioned to overcome the barriers posed by accelerated digital transformation by enhancing their technology infrastructure and reducing financial and technical risks.

Also, dividing the barriers into specific groups improves understanding of their interdependencies. Such classification allows managers to decide which barriers to focus on separately and which to focus on jointly. The framework outlines short-term barriers and proposes ways to address long-term changes in the AFSC.

6.1 Limitations and Future Scope

Our study has limitations that need to be recognized, as with any other research. First, the generalizability of our findings is limited because we primarily gathered data from the Indian agri-food sector. Future studies may employ extensive surveys to gather information from other countries or areas that are actively investigating I4.0 technologies. This could encourage comparisons across cultures and offer greater insight into the underlying motivators. Secondly, the current research does not differentiate among agri-food business sectors (e.g., meat processing vs canning). Therefore, the understanding of the specific sectors could be reduced. Future research should incorporate data from agricultural, animal husbandry, and aquaculture enterprises to develop a more comprehensive understanding of how I4.0 might impact the AFSC.

Third, we used ISM and Fuzzy-MICMAC, two Multi-Criteria Decision-Making (MCDM) approaches, to analyse the barriers. Other MCDM techniques could be used to improve and expand our analysis. The Best-Worst Method, for example, may be used to determine which barriers are most and least desirable. Another method for ranking and choosing among a group of barriers is the VIKOR (Vlekkriterijumsko

KOmpromisno Rangiranje) technique. Further developments in the research can be achieved by leveraging additional decision-making skills and applying the model to different regional and industrial settings. Furthermore, our understanding of the dynamic links between technology uptake and sustainability outcomes should be strengthened through additional empirical validation and cross-sector comparisons. On balance, this work makes substantial contributions not only to the academic literature but also to the practical approach to building a robust digital AFSC.

Conflicts of Interest

For this publication, the author confirms that there are no conflicts of interest to declare.

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AI Disclosure

During the preparation of this manuscript, the authors used generative AI solely to improve the language and readability of the manuscript. After using this tool, the authors carefully reviewed and edited the content as needed and take full responsibility for the content of the publication.

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