Received: 7 March 2024 | Revised: 12 July 2024 | Accepted: 1 August 2024

DOI: 10.1002/bse.3928

RESEARCH ARTICLE

Business Strategy and the Environment WILEY

Analysis of barriers to adopting Industry 4.0 to achieve agri-food supply chain sustainability: A group-based fuzzy analytic hierarchy process

Guoqing Zhao[1] | Chenhui Ye[2] | Denis Dennehy[1] | Shaofeng Liu[3] | Antoine Harfouche[4] | Femi Olan[5]

[1]School of Management, Swansea University, Swansea, UK

[2]IRIT, Toulouse Université, Toulouse, France

[3]Plymouth Business School, University of Plymouth, Plymouth, UK

[4]University Paris Nanterre, Paris, France

[5]Essex Business School, University of Essex, Colchester, UK

Correspondence
Guoqing Zhao, School of Management, Swansea University, Swansea, UK.
Email: guoqing.zhao@swansea.ac.uk

Abstract

Agri-food supply chains (AFSCs) need to become more sustainable, and Industry 4.0 (I4.0) is a crucial enabler. However, various barriers make adopting I4.0 technologies to achieve AFSC sustainability challenging. Few previous studies have examined China's agri-food industry. Through a literature review and consultation of Chinese experts, we identify 27 barriers in six categories and prioritize these using a group-based fuzzy analytic hierarchy process to produce novel results. First, we identify six new I4.0 adoption barriers closely linked with China's economic, social and cultural environments, including acquisition of intelligent agricultural equipment subsidies based on *guanxi*. Second, our prioritization of barriers reveals that the key challenges to applying I4.0 are the increased cost of terminal logistics, acquisition of intelligent agricultural equipment subsidies based on *guanxi*, low compatibility of I4.0 technologies with existing agricultural equipment, and problems with the government subsidy model. These results have managerial implications for governments and knowledge dissemination organizations.

KEYWORDS

agri-food supply chain sustainability, barriers to identification and prioritization, China's economic, grand theory, group-based fuzzy analytic hierarchy process, Industry 4.0 adoption, social and cultural environments

1 | INTRODUCTION

Agri-food supply chains (AFSCs) encompass processes from farm to fork, including production, processing, wholesale distribution, retailing and consumption (Zhao et al., 2023). Scholars and industry practitioners widely recognize AFSCs' critical roles as suppliers of sufficient, high-quality and affordable foods to final consumers, providers of raw materials to other industries (e.g., pharmaceuticals, textiles, hospitality, beverages and chemicals) and the backbone of national economies and workforce employment. They also play a role in

Abbreviations: AFSCs, agri-food supply chains; AI, artificial intelligence; AJG, academic journal guide; ANP, analytic network process; AR, augmented reality; CABS, Chartered Association of Business Schools; CE, circular economy; CoCoSo, combined compromise solution; CR, consistency ratio; CT, contingency theory; DEMATEL, decision-making trial and evaluation laboratory; ELECTRE, elimination and choice expressing reality; FAO, Food and Agriculture Organization of the United Nations; GFAHP, group-based fuzzy analytic hierarchy process; GT, grand theory; I4.0, Industry 4.0; ICTs, information and communication technologies; IoT, internet of things; IRP, interpretive ranking process; ISM, interpretive structural modelling; MCDM, multi-criteria decision-making; RBV, resource-based view; TBL, triple bottom line; TCE, transaction cost economics; SLRs, systematic literature reviews; SSCM, sustainable supply chain management; SWARA, step-wise weight assessment ratio analysis; USDA, United States Department of Agriculture; VR, virtual reality.

reducing the impacts of climate change (FAO, 2022). However, natural, economic and social environmental pressures are making sustainability more difficult to achieve. For example, extreme weather conditions are causing unstable yields, consumers' awareness of and demand for organic agri-food products is increasing, excessive use of agrichemicals is leading to deterioration of soil, groundwater and biodiversity, high pesticide residues may damage human health, and long working hours cause anxiety and depression among employees (Joshi et al., 2023). Demand for advanced agricultural technologies is increasing and may assist AFSC practitioners in tackling current and future challenges.

Industry 4.0 (I4.0) technologies are characterized by automation, flexibility, productivity, efficiency and customization. They include emerging technologies such as the internet of things (IoT), artificial intelligence (AI), augmented/virtual reality (AR/VR) and industrial robots (Ghobakhloo, Fathi, et al., 2021; Prajapati et al., 2024; Singh et al., 2024). These technologies have great potential to significantly increase AFSCs' sustainability. For example, agricultural robotics can be used for harvesting and picking, sorting and packaging and weed control (Yang et al., 2023); IoT is applied to agricultural management, monitoring and control systems (Kim et al., 2020); and blockchain technology helps to achieve AFSC transparency (Zhao et al., 2019). I4.0 technologies integrate machines, people and data, producing healthier crops, higher yields, better cost management, waste reduction and smaller carbon footprints, thereby contributing to AFSC sustainability. Awan et al.'s (2023) analysis of 112 peer-reviewed papers in this field reveals that scholars recognize the importance of I4.0 and sustainability and have produced a rich body of knowledge. However, forms of I4.0 technologies and sustainable practices vary widely between different types of supply chains. Accordingly, Awan et al. (2023) call for further research to enrich the debate on I4.0 and sustainability across operations and supply chain management.

Although AFSCs' adoption of I4.0 technologies promises a range of benefits, the trend is in its infancy. I4.0 techniques are still at the early-adoption stage and their implementation requires further exploration (Ul-Durar et al., 2023). In Molex's (2021) survey of 216 AFSC stakeholders, only 6% had successfully deployed I4.0 solutions and 12% were about to do so. Deloitte's (2020) global annual survey of agricultural businesses' preparedness for a connected era indicates that among 12 investment priorities, only 17% of chief experience officers prioritize I4.0 technology investment. Interestingly, none of the 200 executives surveyed by Deloitte recognized the potential of I4.0 technologies to advance societal and environmental initiatives, indicating a need for research on I4.0 technologies and AFSC sustainability. Based on a survey of more than 5500 crop farmers globally, McKinsey and Company (2023) develops a global agri-tech adoption map, showing that 62% of farmers in Europe, 61% in North America and 50% in South America were already using or planning to use farm-management software and remote sensing in the next 2 years. In contrast, only 9% of surveyed Asian farmers were planning to do so. With regard to other precision agriculture technologies, such as yield monitoring and mapping, variable rate fertilizer application, sprayer section controllers and in-field sensors, more European, South American and North American farmers (approximately 28%) expressed willingness to adopt these technologies in the next few years, compared with only 4% of Asian farmers. Asian farmers' willingness to apply agri-tech was hampered by a range of barriers, the top three of which were reluctance to pay, the high cost of technology and unclear returns on investment. A report on the future of I4.0 in Wales (National Assembly for Wales, 2018) indicates the main challenges to applying I4.0 in agriculture. These include difficulties in interpreting data produced by I4.0 technologies, the amount of training and skilling needed, additional management time required to take-up precision agriculture, lack of good 5G and broadband coverage, the technologies' impact on agricultural employment and ethical issues involved in manipulating data. As I4.0 adoption is complex and dynamic (Kamble et al., 2018), empirical research on I4.0 adoption barriers in different countries may elicit effective mitigation strategies to smooth the adoption process. Based on a review of 109 papers published between 2011 and 2021 focusing on the digital and sustainable transition of the agri-food sector, Abbate et al. (2023) recommend further exploration of barriers to implementing I4.0 and sustainability. In our study, we aimed to address this issue by answering two research questions: (1) what barriers impede I4.0 adoption to achieve AFSC sustainability; and (2) how are these barriers prioritized? To answer the first question, grounded in grand theory (GT), we reviewed relevant literature and consulted 10 Chinese experts to identify 27 I4.0 adoption barriers. GT differs from other theories because it aims to identify cause-and-effect relationships that can be broadly applied to other similar situations, contexts or phenomena of interest (Zhao, Zhao, et al., 2024). To answer the second question, we adopted a group-based fuzzy analytic hierarchy process (GFAHP) to prioritize the 27 barriers based on the judgements of three experts. A GFAHP was implemented because human estimations are uncertain and vague, and it is difficult for a single decision maker to make reliable decisions (Che et al., 2020). Our study appears to be the first to use GT to identify barriers in macro-level environments, meso-level AFSCs and micro-level organizations, and the first to apply a GFAHP to prioritize barriers.

Our study makes several theoretical contributions. First, we contribute to GT by identifying six new I4.0 adoption barriers deeply relevant to China's cultural, economic and social environments seldom mentioned by other scholars (Cui et al., 2021). These include acquisition of intelligent agricultural equipment subsidies based on *guanxi*, problems with the government subsidy model and lack of non-profit knowledge brokers to transfer knowledge and skills. In similar studies, Kumar, Singh et al. (2021) identify 15 barriers to sustainable operations in the era of I4.0 and circular economy (CE), including lack of a skilled workforce and an ineffective performance framework; Mathivathanan et al. (2021) consider barriers to the adoption of blockchain technology in business supply chains such as lack of business awareness; and Dwivedi and Paul (2022) produce a barrier framework for digital supply chains in the era of CE by seeking the opinions of five experts from different industrial backgrounds. These studies provide understandings of barriers to adopting I4.0 technologies to achieve sustainability from a general rather than context-specific perspective, limiting the insights obtained. Second, existing studies of I4.0

adoption barriers prioritize technological and economic categories (Govindan et al., 2014; Mathiyazhagan et al., 2013; Nimawat & Gidwani, 2021). In contrast, we conclude that environmental and supply chain barriers should be given critical attention. Third, lack of government support, the high costs of investing in I4.0 technologies and lack of trained staff are widely discussed as key barriers to I4.0 adoption (Senna et al., 2022). However, we conclude that the top four barriers in our context are the increased cost of terminal logistics, acquisition of agricultural equipment subsidies based on *guanxi*, incompatibility with existing agricultural equipment and problems with the government subsidy model. Our study also has managerial implications, highlighting that non-profit knowledge mobilization organizations are required and that the government should subsidize intelligent agricultural equipment manufacturers that have wide connections with farmers and research institutes.

In the remainder of this article, in Section 2 we review relevant literature, and in Section 3 we describe our research methodology. In Section 4, we present our analysis of data collected by reviewing the literature and consulting experts, and our prioritization of barriers using a GFAHP. In Section 5, we discuss the theoretical contributions and managerial implications of our study, and in Section 6, we draw conclusions and discuss limitations and future research directions.

2 | LITERATURE REVIEW

In this section, we review five key themes: GT to build a theoretical foundation for this study; characteristics of China's agri-food industry; I4.0 technologies and their applications in AFSCs; AFSC sustainability in the era of I4.0; and barriers to deploying I4.0 technologies to achieve supply chain sustainability. Our findings are then synthesized to identify research gaps.

2.1 | Grand theory

Several theories have been widely used to investigate supply chain and logistics issues, including the resource-based view (RBV), dynamic capabilities, contingency theory (CT), stakeholder theory, institutional theory, transaction cost economics (TCE) and social network theory. For example, Ren et al. (2023) deploy the RBV to build a technology transfer model that adheres to CE principles, and McAdam et al. (2019) employ CT to explore supply chain quality management. These general theories are useful for exploring supply chain phenomena at a high level of abstraction, but fall short in linking the phenomena with wider contexts. This made them inappropriate for our study, as achieving sustainability by adopting I4.0 technologies is a tough issue that requires synergies across various aspects, including culture and mindset, technological requirements, infrastructural framework, economic incentives and market enablement and the regulatory environment (European Environment Agency., 2021). GT differs from these general theories in postulating that all social issues occur because of forces operating at all levels of social reality. The more of reality examined, the more 'grand' is the theory. GT is a unified theory that aims to capture every aspect of the phenomenon being investigated. It can be considered as a 'guide', a 'big picture' or a 'map' to orient research (Turner & Boyns, 2002). A GT is broad in scope, providing a comprehensive framework to explain complex phenomena by emphasizing broad perspectives.

We employed GT to investigate I4.0 adoption barriers for three reasons. First, GT seeks to identify essential environmental and/or organizational variables that may help understand the phenomenon being investigated (Sanchez & Heene, 2017). More specifically, it aims to uncover cause-and-effect relationships that can be broadly applied to all cases and contexts in the field of study. In our opinion, a comprehensive understanding of I4.0 adoption barriers can only be obtained by analysing barriers at the macro-, meso- and micro-levels of environments, supply chains and organizations. Our study focuses on China, the unique economic, cultural and social environments of which provided us with a foundation for linking this context with I4.0 adoption barriers. For example, China's hierarchical cultural value orientation leads people to seek to build connections with key government officers who have power to control resources. This cultural environment elicits I4.0 adoption barriers such as acquisition of intelligent agricultural equipment subsidies based on *guanxi*, and lack of non-profit knowledge brokers to transfer knowledge and skills. Our second reason for using GT was that it is a well-developed theory that has been used to facilitate theory-driven research. For example, Turner and Boyns (2002) propose that the social landscape should be explained by linking macro- and micro-levels of reality. According to Widodo (2018), GT seeks to provide an overarching framework for understanding the complexities of management. Third, GT has seldom been used to investigate supply chain management issues. For example, Gligor et al.'s (2019) review of 411 articles published in six top supply chain management journals over the last ten years indicates that 15 theories are frequently used to explore supply chain management issues. These include RBV, TCE, agency theory, social capital theory and relational exchange theory, but not GT. From a structured review of sustainable supply chain management, Touboulic and Walker (2015) reach a similar conclusion. Thus, we adopted GT to

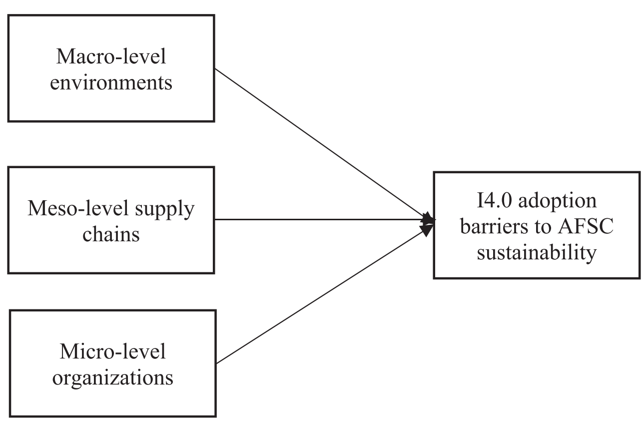

FIGURE 1 The theoretical framework of I4.0 adoption barriers.

investigate barriers to I4.0 adoption to achieve AFSC sustainability. Our theoretical framework is shown in Figure 1.

2.2 | Characteristics of China's agri-food industry

China's agri-food industry differs in several aspects from other industries, and thus warrants empirical investigation. First, over the last four decades, young people have migrated from rural to urban areas. Urbanization in China has increased steadily from 19.39% in 1980 to 65.22% in 2022 (Guo et al., 2022), causing labour shortages and an ageing workforce in China's agri-food industry. According to a recent global agricultural productivity report, more than 60% of agri-food industry practitioners in China are over 45 years old, whereas only 14% are under 35 years old. Second, Chinese consumers' preferences and food consumption patterns are changing with the rise of the middle class. China has the most middle-class families in the world, with 57.02% having an annual income of between 100 and 300 thousand yuan (Sicular et al., 2022). Middle-class families' increasing incomes enable them to pay more attention to high-quality, organic, low pesticide residue agri-food products, thereby forcing a transformation of traditional agriculture. Third, China uses 7% of global arable land and 6% of water resources to support 20% of the world's population. However, over 92% of farms in China are small, with less than 0.1 ha of land (Zhu et al., 2019), precluding the operation of large-scale agricultural technology. Fourth, agri-food logistics, e-commerce platforms and grocery shopping have grown steadily with continuous investment in infrastructure, yet bottlenecks in logistics capabilities persist. Finally, agri-food products are perishable, so special equipment, such as cold storage and refrigerated trucks, is required for their transportation and storage (Zhao et al., 2020).

To address these widespread issues in China's agriculture, rural areas and farms, the government is focusing on revolutionizing the agri-food industry. For example, the 14th Five-Year Plan proposes to achieve agricultural modernization between 2021 and 2025. Thus, policies have been established to support the development of modern agricultural equipment and advanced technologies (State Council., 2021). I4.0 technologies have the capability to improve product quality, reduce operational costs, increase productivity and enhance sustainability and are therefore considered key to revitalizing China's agri-food industry.

2.3 | Applications of I4.0 technologies in AFSCs

The concept of I4.0 was originally proposed to revolutionize the manufacturing industry by using advanced information and communication technologies (ICTs). It was developed to connect and link assets, products and people by breaking intra- and inter-organizational boundaries, thereby establishing a new industrial production ecosystem that combines the physical and virtual world (Xu et al., 2018). Several design principles have been established for I4.0 (Canas et al., 2021; Qin et al., 2016). Interconnection or connectivity refers to linking digital devices by deploying ICTs. Decentralized decision making involves making decisions automatically in real time by installing artificial agents in production, planning and management processes. Intelligent awareness or autonomy means that machines must be equipped with self-awareness and the capability to provide assistance, knowledge or help to fulfil group goals. Human factors also play a critical role in implementing technological and organizational methods to achieve control and production targets (Parente et al., 2020). Based on these principles, various I4.0 technologies have been developed, combined and applied in supply chains to achieve high operational efficiency, productivity, customization, profitability, safety and automation. Queiroz et al. (2021) identify six core I4.0 technologies, Gebhardt et al. (2022) identify eight and Dalenogare et al. (2018) identify ten, indicating a lack of consistency and scholarly agreement on I4.0 technologies. This may be due to research interests in specific industries, such as manufacturing, health or agri-food, with limited understanding of applying I4.0 technologies to other industries with differing requirements. As a result of synthesizing literature reviews relating to I4.0 and supply chain management, we identify 10 frequently mentioned I4.0 technologies: cyber-physical systems, IoT, big data analytics, cloud technology, AI, blockchain technology, simulation and modelling, AR/VR, automation and industrial robots, and additive manufacturing (Awan et al., 2021; Zheng et al., 2021).

I4.0 technologies can also be applied to AFSCs to achieve sustainable and precision farming, waste reduction, enhanced food safety and quality, and improved traceability. For example, at the farming stage, sensors, IoT and mobile software are combined to understand soil composition and measure soil nutrition, temperature and moisture; drones, global positioning systems (GPS), satellite imaging and programmes are integrated to monitor crop health; and big data analytics are used to predict weather and improve farming operations (Cotter & Asch, 2020). At the manufacturing stage, robotics, IoT, sensors and AI are integrated for packaging and palletizing, to increase production efficiency and capacity, and to reduce labour and production costs (Aly et al., 2023), and AR/VR is used to provide an enhanced learning environment to enable new employees to master skills and knowledge (Akcayir & Akcayir, 2017). At the distribution stage, radio frequency identification, IoT, blockchain technology, GPS and sensors are employed for secure transactions and food tracking (Zhao et al., 2019), and AI and big data analytics are used to optimize logistics and reduce transit time (Bouzembrak et al., 2019). Finally, at the retailing and consumption stages of AFSCs, mobile software, big data analytics, AI and machine learning are combined to personalize agri-food product recommendation (Misra et al., 2022). Figure 2 illustrates I4.0 technology-enabled AFSCs.

2.4 | AFSC sustainability in the I4.0 era

Sustainability refers to 'development that meets the needs of the present without compromising the ability of future generations to meet their needs' (World Commission on Environment and Development, 1987, p. 8). This widely cited definition emphasizes the economic

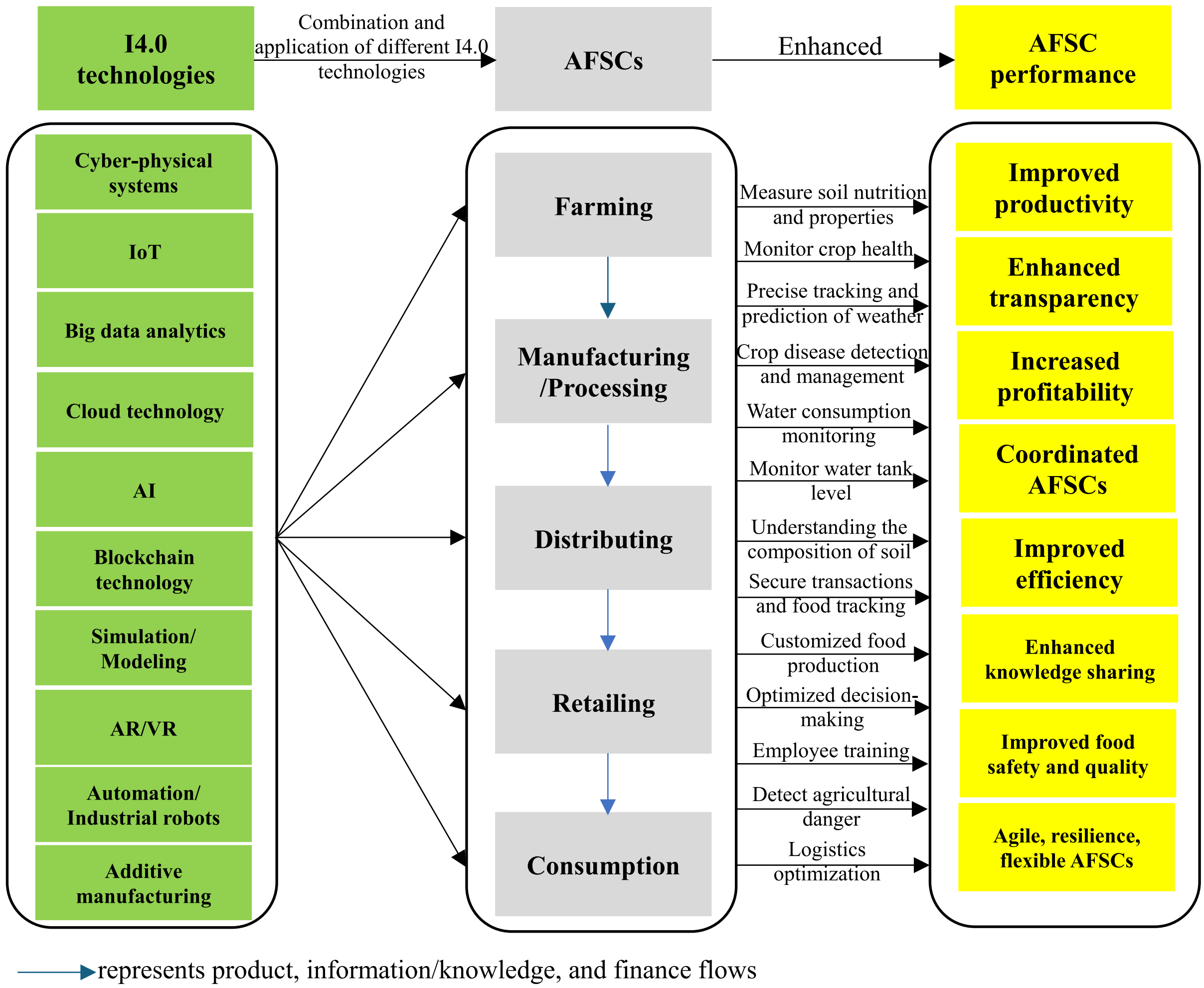

FIGURE 2 I4.0 technology-enabled AFSCs.

dimension of sustainability, but provides little guidance on how to achieve it, making it difficult for organizations to apply. Elkington's (1997) triple bottom line (TBL) explicitly incorporates three main components into sustainability: social, economic and environmental. This enhanced concept has been applied to various areas. For example, in agriculture, USDA (2023) defines sustainable agriculture as a system that is environmentally friendly, socially supportive, commercially competitive and resource conserving, with the capability to satisfy humans' long-term food and fibre needs. In engineering, sustainability is described as using resources and materials efficiently with minimal environmental impact while also cutting costs (Hasna, 2010). In business and management, numerous definitions are proposed for SSCM. For example, Carter and Rogers' (2008) definition is based on the TBL and four supporting facets of sustainability identified from the literature (risk management, transparency, strategy and culture). This indicates that the supply chain's social, economic and environmental goals are achieved through a transparent, systematic, strategic process of integrating and coordinating stakeholders' business processes, thereby providing long-term economic benefits to supply chains and individual companies. Ahi and Searcy's (2013) alternative definition focuses on SSCM as a process for creating a coordinated supply chain by integrating social, economic and environmental considerations with critical inter-organizational processes. They also support the aims of fulfilling stakeholders' requirements and enhancing supply chain organizations' long-term profitability, competitiveness and resilience. These definitions provide little understanding of AFSC sustainability because they focus on general supply chains rather than specific characteristics of AFSCs, and suggest that social, economic and environmental dimensions are equally important to sustainability (Martins & Pato, 2019). However, we believe that the environmental dimension should take precedence over the social and economic dimensions (Markman & Krause, 2016) because most agri-food activities affect the former, including intensive agriculture, deforestation to expand farms, excess use of water and agrichemical products, and soil and air pollution. The FAO's (2014, p. 6) definition provides a better foundation for understanding AFSC sustainability: 'the full range of farms and firms and their successive coordinated value-adding activities that produce particular raw agricultural materials and transform them into particular food products that are sold to final consumers and disposed of after use, in a manner that is profitable throughout, has broad-based benefits for society and does not permanently deplete natural resources'.

Since AFSCs' complexity and multiple challenges present obstacles to tackling poverty and hunger issues, I4.0 technologies are being applied to AFSCs to create pathways to sustainability. According to the FAO (2023), the only feasible way to continuously increase crop and livestock productivity to eliminate hunger without damaging natural environments is to accelerate the application of I4.0 technologies to the agri-food industry. Among several research streams investigating AFSC sustainability in the era of I4.0, the first explores applications of I4.0 technologies to strengthen the economic pillar of AFSC sustainability. This includes papers relating to 'value creation', 'cost saving', 'productivity' and 'investment' in AFSCs' I4.0 technology adoption (Piccarozzi et al., 2022). For example, various I4.0 technologies are applied to the farming stage of AFSCs (e.g., crop monitoring, irrigation management, decision support and automation) to enhance efficiency and productivity and reduce operational costs (Nawandar & Satpute, 2019), and blockchain technology is used at the distribution stage to enhance food traceability (Feng et al., 2020). In the second research stream, I4.0 technologies are linked with the environmental dimension of AFSC sustainability using key phrases such as 'pollution control', 'energy efficiency', 'greenhouse gas management' and 'environmental impacts' (Lu et al., 2024). For example, Mahajan et al. (2022) propose AI-based smart farming to reduce farms' energy consumption, and Liu et al. (2023) suggest that applying digital technologies may reduce dairy farms' carbon emissions. Third, in relation to the social dimension of AFSC sustainability, most papers analyse the social impact of I4.0 technologies and their application to reduce pressures on human resource management (Cricelli et al., 2024; Stefanini & Vignali, 2022). A fourth important research stream relating to I4.0 and AFSC sustainability is the CE and food waste reduction. Frequently used keywords in this area include 'recycling', 'waste disposal', 'waste management', 'circular economy', and 'food loss'. For example, Kumar, Singh et al. (2021) identify barriers to adopting I4.0 and a CE in AFSCs, and Cappelletti et al. (2022) explore smart strategies for household food waste management. Other papers focus on business model innovation, the customer domain of AFSCs, government policies and approaches, and the impacts and challenges of applying I4.0 to achieve AFSC sustainability (Agnusdei & Coluccia, 2022).

2.5 | Barriers to I4.0 technology deployment to achieve supply chain sustainability

In this section, we present our systematic literature review (SLR) to identify barriers to adopting I4.0 to achieve supply chain sustainability. Keywords used in previous SLRs (Piccarozzi et al., 2022; Srhir et al., 2023) pertaining to the areas of I4.0 and SSCM were combined and used as search criteria in titles, keywords and abstracts using Business Source Complete, Taylor & Francis Online, and Science Direct. We selected these databases because they have large collections of social sciences and humanities journals, cover a wide range of business and management topics and are easily accessed. We combined keywords as search strings for our database search: ('I4.0' OR 'Digital technology' OR 'Smart technology' OR 'Smart production' OR 'Supply chain 4.0') AND ('Barriers' OR 'Challenges' OR 'Difficulties' OR 'Limitations' OR 'Obstacles' OR 'Inhibitors' OR 'Risks') AND ('Supply chain sustainability' OR 'Sustainable supply chain' OR 'Sustainable development' OR 'Circular supply chain' OR 'Circular economy' OR 'Sustainable supply chain management'). Our initial search across the three databases produced 386 journal papers in English. We then applied criteria to limit the scope for further analysis. First, the papers had to be published in journals rated 3 or above in the 2021 Academic Journal Guide (AJG), indicating journals with an excellent international reputation that publish mainly original and high-quality research (CABS, 2021). AJG encompasses a broad set of business and management journals and aims to help researchers to make informed judgements about the outlets they may wish to publish in (CABS, 2021). However, journals not listed in the AJG 2021 ranking but with a high impact factor were also considered. In general, there is no universally applied rules to define a high impact factor journal because it depends on the discipline and the specialization of the journal. However, a journal with an impact factor of 10 or higher is considered as remarkable. In this study, we considered journal's impact factor and its ranking to make inclusions. For example, *Resources, Conservation & Recycling* was included because it had an impact factor of 13.716 and was ranked fourth in the area of engineering and environmental sciences in 2021. Second, the selected papers had to have a clear focus on 'barriers', 'I4.0' and 'sustainable supply chain'. Thus, we excluded papers focusing on 'I4.0 adoption barriers without referring to sustainability', 'enablers of I4.0 applications', 'deployment of I4.0 to address sustainability challenges' or 'I4.0 to improve SSCM performance', or that 'linked I4.0 and sustainability or the circular economy without stating barriers'. Papers not published in journals rated 3 or above in the AJG 2021 were also excluded, including those papers in *Sustainability*, *Journal of Cleaner Production*, *Computers & Industrial Engineering*, *Sustainable Production and Consumption* and *Benchmarking: An International Journal*. This resulted in 13 papers for detailed analysis. We then analysed the selected papers based on the industries, topics and countries on which they focused, the research methodologies adopted, the multi-criteria decision-making (MCDM) techniques used, and the barriers identified (see Table 1).

We allocated the barriers to six dimensions through checking relevant papers and discussing with experienced scholars: technological, economic, environmental, social, supply chain and organizational. The first four are relevant to macro-level environments, and the last two are relevant to meso-level supply chains and micro-level organizations. Trevisan et al. (2023) categorize barriers into eight dimensions (knowledge management, financial, process management & governance, technological, product & material, reverse logistics infrastructure, social behaviour, and policy & regulatory), while Kouhizadeh et al. (2021) classify them into four categories: technological, organizational, environmental (supply chain) and environmental (external). Unlike previous studies, to explore barriers to adopting I4.0 for AFSC sustainability, our categorization relates to the three pillars of sustainability, characteristics of AFSCs and features of I4.0 technologies.

TABLE 1 Papers and barriers identified from SLR.

Author(s) (year)	Industry focus	Topic focus	Research methodology adopted	MCDM technique used	Country focus
Abdul-Hamid et al. (2020)	Agri-food	Impediments to I4.0 in circular economy	Modelling paper	Fuzzy Delphi and ISM	Malaysia
Ozkan-Ozen et al. (2020)	Not specified	Barriers to circular supply chains in I4.0	Modelling paper	Fuzzy ANP	Turkey
Shuvabrata et al. (2020)	Logistics	Barriers to achieving sustainable operations through IT implementation	Modelling paper	Fuzzy ISM and IRP	India
Annosi et al. (2021)	Agri-food	Digitalization of AFSCs to prevent food waste	Case studies/ Interviews	N/A	Greece
Cui et al. (2021)	Manufacturing	Barriers to IoT adoption for the circular economy	Modelling paper	SWARA-CoCoSo	China
Kouhizadeh et al. (2021)	Agri-food	Barriers to blockchain technology adoption to achieve SSCM	Modelling paper	DEMATEL	N/A
Kumar, Singh et al. (2021)	Manufacturing	Barriers to integrating sustainable operations and I4.0	Modelling paper	ELECTRE and AHP	India
Majumdar, Garg, and Jain (2021)	Textile and clothing	Managing barriers to I4.0 adoption and implementation	Modelling paper	ISM	India
Dwivedi et al. (2022)	Footwear	Barriers to integrating circular economy and I4.0	Modelling paper	Gray-DEMATEL	India
Govindan (2022)	Automotive	Barriers to adopting blockchain in circular manufacturing	Modelling paper	DEMATEL	Denmark
Mangla et al. (2022)	Agri-food	Barriers to implementing blockchain-based sustainable supply chains	Modelling paper	Spherical fuzzy AHP	Turkey
Yilmaz et al. (2022)	Not specified	Lean and I4.0: Mapping barriers from social and environmental perspectives	Literature review	N/A	N/A
Trevisan et al. (2023)	Multi-industries	Barriers to employing digital technologies for a circular economy	Case studies/ interviews	N/A	Brazil
Journals	*Industrial Marketing Management* (AJG3), *International Journal of Production Economics* (AJG3), *Business Strategy and the Environment* (AJG3), *Technological Forecasting & Social Change* (AJG3), *Computers & Operations Research* (AJG3), *Journal of Environmental Management* (AJG3), *Resources, Conservation & Recycling*				
Barriers identified from papers					
Technical	Lack of technological development, limited information about infrastructure, information sharing obstacles, lack of privacy risk, scalability, forking, payment channel challenges, lack of data for analysis, unreliability of technology, poor internet connection, stakeholders' lack of knowledge of data management, lack of IoT facilities for product tracking and recovery, transition to digital technologies requires people who are competent in both the new technologies and the firm's operations, security challenge, access to technology, immaturity of technology, technological suitability and resistance, lack of knowledge of good environmental practices, technology still requires human observation, lack of technological adaptation, large amounts of paperwork that are difficult to computerize, lack of generalized framework				
Economic	High operational costs, high investment costs, lack of financial subvention, high delay cost in transmission, increased consumer costs, unapparent short-term returns, insufficient tax benefits, unperceived environmental and economic gains, risk of mis-investment				
Social	Lack of research and development units, unregistered producers, unskilled producers, limitation of new rules acceptance, low labour costs, psychological resistance, lack of awareness, fear of fraudulent activity				
Environmental	Lack of government incentives, difficulty accessing foreign currency, lack of sustainable practices, lack of government commitment, lack of industry involvement, lack of circular design aspect, threat of environmental hazards, reduced employment, little government inspection and control, lack of market pressures and demands, market uncertainty, ineffective performance framework				
Organizational	Lack of understanding of decentralized organizational structure for supplier collaboration, lack of organizational willingness and trust in transformation of I4.0 and circular flows, lack of management commitment and support, difficulty in changing organizational culture or convincing management, lack of integration of company areas				
Supply chain	Product-specific supply chain difficulties, lack of trust among supply chain partners, limited collaboration among supply chain partners, perception of new risks potentially affecting stakeholders along the supply chain, cultural differences in supply chain partners, lack of local supplier databases, lack of knowledge of how to digitalize supply chains				

2.6 | Synthesis of research gaps

Our literature review highlights several research gaps.

First, few papers ($n = 4$, 30.77%) focus on the agri-food industry. This result is consistent with previous literature reviews. For example, Taddei et al. (2022) find that only 11 out of 198 papers published between 2010 and 2021 on circular supply chains in the I4.0 era focus on the agri-food industry. Similarly, Birkel and Muller's (2021) SLR on I4.0 and SSCM reveals that manufacturing industries have been extensively investigated, but the agri-food and healthcare industries require more detailed attention. Our study fills this gap.

Second, our analysis shows that China has received little scholarly attention, as only one selected paper focuses on China. This is also consistent with previous literature reviews. For example, Ghobakhloo, Iranmanesh et al. (2021) review of 10 years of development of I4.0 and sustainability indicates that Germany has attracted the greatest attention, followed by Italy, the United Kingdome, India, the United States and China. Taddei et al. (2022) show that Indian authors have contributed most to the area of the circular economy and I4.0, followed by authors from the United Kingdom, Italy, Germany, Brazil, Spain and China. Piccarozzi et al.' s (2022) 10-year review also reveals that India has made the most important contributions, followed by Germany and China. China feeds a fifth of the world's population with less than 7% of the world's arable land, and produces the most cereals, cotton, fruit, vegetables and meats, so its agri-food industry deserves greater attention. Our study fills this gap.

Third, modelling is the prevalent research methodology used to analyse barriers. Specific techniques include interpretive structural modelling (ISM), decision-making trial and evaluation laboratory (DEMATEL), analytic network process (ANP), analytic hierarchy process (AHP) and fuzzy Delphi (see Table 1). However, few scholars have used GFAHP, which differs from traditional AHP in involving multiple decision makers in weighting multi-criteria decisions (Coffey & Claudio, 2021). Our study advances this area by applying GFAHP to analyse barriers.

3 | RESEARCH METHODOLOGY

In this study, we adopted a mixed-method approach (see Figure 3) that combines qualitative and quantitative data collection and analysis in one study to identify and prioritize barriers for several reasons (Creswell, 1999). First, this approach enhances interpretation and understanding by exploring the findings from one method using the results from another (Timans et al., 2019). Second, it elicits a rich and deep dataset by analysing data from different research angles, helping to capture the diversity and complexity of the research phenomenon (Doyle et al., 2009). Finally, it improves the quality and rigour of research by balancing the strengths and limitations of different approaches (Halcomb, 2019). Thus, qualitative and quantitative methods were combined in the two separate research phases of identifying and prioritizing barriers.

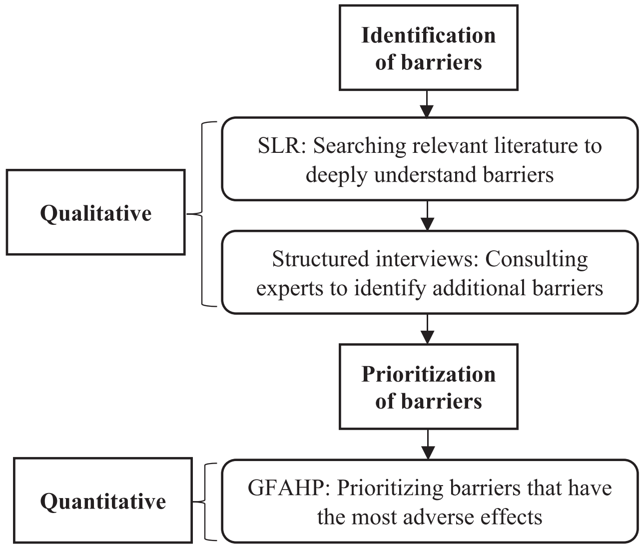

FIGURE 3 Research methodology employed.

At the barrier identification stage, we used an SLR and structured interviews. This combination has previously been used to identify barriers to I4.0 adoption, providing us with some confidence to apply it in this study. For example, Majumdar, Garg, and Jain (2021) conduct an extensive literature review to identify 22 barriers to I4.0 adoption and implementation in the textile and clothing industry and then use structured interviews to evaluate and identify other barriers. Sarkar and Shankar (2021) identify 18 barriers to the effective operation of port 4.0 utilizing a literature review and expert consultation. Accordingly, our SLR was used to conduct an exhaustive search for relevant journal papers to provide us with a deep understanding of barriers to I4.0 adoption, resulting in the identification of more than 60 barriers. We then employed structured interviews to evaluate these barriers and identify any additional barriers in China's ASFCs. Structured interviews were selected for three reasons. First, they are a powerful method for understanding and generating new ideas (Saunders et al., 2009), which might help us to identify new barriers, particularly as we were investigating a topic in which knowledge is accumulating. Second, industry experts prefer to answer oral questions rather than filling in questionnaires (Zhao, Xie, et al., 2024). Third, the standardization of structured interviews helps to minimize contextual effects.

At the barrier prioritization stage, we applied GFAHP because it offers several advantages. First, in the digital era, decisions are rarely made by a single decision maker. GFAHP utilizes opinions from multiple decision makers, which better reflects real-world decision-making problems (Coffey & Claudio, 2021). Second, GFAHP helps to structure complex decision-making problems by listing goals, criteria and alternatives, and is a powerful, widely used technique (Che et al., 2020; Dyer & Forman, 1992; Zhu & Xu, 2014). Third, it has clear steps to follow, and can generally be categorized into the three steps of modelling, prioritization and synthesis. However, it does have limitations. A critical drawback is that it may be difficult to reach consensus among large groups of decision makers (Tang & Liao, 2021). To alleviate this, we selected three experts with extensive decision-making experience to rate relationships between pairs of barriers. Other MCDM methods for ranking or prioritizing barriers could not be applied in this study owing to their shortcomings. For example, ISM is effective for determining key alternatives, but does not weight or rank these options (Sushil., 2012), whereas GFAHP is effective for prioritizing alternatives by calculating the weighting of each. AHP and fuzzy AHP can be used to determine the relative importance of alternatives, but in most situations, the prioritization results are based on a single expert's opinion. GFAHP differs in allowing a group of experts to express their judgements independently in fuzzy linguistic terms, an approach that has proved to be more realistic for tackling real-life decision-making problems (Wang & Elhag, 2007). The interpretive ranking process (IRP) has limited applicability because judgements may be highly subjective. DEMATEL is useful for revealing cause-and-effect relationships and ranking variables, but does not take account of the relative weightings of multiple experts involved in a decision-making problem (Si et al., 2018). GFAHP has advantages over IRP and DEMATEL because multiple decision makers are involved and their opinions weighted in decision-making problems.

4 | DATA ANALYSIS AND FINDINGS

In this section, we present how we identified and prioritized barriers using a combination of SLR, structured interviews and GFAHP.

4.1 | Barrier identification using SLR and structured interviews

To achieve consistency, we first developed an interview guide that included six dimensions of barriers: technological, social, environmental, economic, organizational and supply chain (see Appendix A). The interview guide was developed through a brainstorming session with several experienced researchers involved in this project. We then conducted pilot interviews with two professors in operations management to determine potential improvements to the interview guide. Their feedback indicated that a brief introduction to the project should be given prior to the interviews, and an 'any other barriers' row should be added to the end of each barrier dimension.

The barriers identified from the SLR (see Table 1) were then evaluated by experienced AFSC practitioners from China. They were selected based on their expertise, knowledge and working experience. Only experts who expressed strong willingness to participate in this project and had been working in the agri-food industry for more than 30 years were selected. Our initial selection based on our connections and relevant expertise resulted in 35 potential respondents, whom we contacted through email and WeChat to check their availability and willingness. Of these, 25 were either unwilling to participate in this project or did not have sufficient working experience or available time. Thus, our final sample consisted of 10 agri-food professionals with the required expertise and experience. During the interview process, these experts were asked to tick 'strongly agree', 'agree', 'neutral', 'disagree' or 'strongly disagree' for each I4.0 adoption barrier that we had identified through the SLR. Barriers ticked as 'neutral', 'disagree' or 'strongly disagree' were eliminated, for several reasons. First, these barriers identified through our SLR were based on studies conducted in countries with differing cultural value orientations, resulting in different environmental, social and supply chain barriers. However, since this study focuses on China, barriers irrelevant to this context were excluded. For example, China's hierarchical cultural value orientation contributes to unequal distribution of power, roles and resources and leads people to reject new realities and view competition as good (Schwartz, 2006). Thus, we included barriers such as psychological resistance to using I4.0 technologies, lack of awareness of applications of I4.0 technologies, reluctance to share knowledge to avoid competition, lack of collaboration with research institutes, and acquisition of intelligent agricultural equipment subsidies based on *guanxi*. Second, I4.0 adoption barriers are also affected by other factors, such as countries' levels of technological development, agri-food industry practitioners' education levels and demographic status, and agriculture-related infrastructure. Based on the experts' opinions, 16 barriers relevant to China's context were included for further analysis. At the end of each interview, we asked interviewees to specify any other I4.0 adoption barriers relevant to China's unique contexts, resulting in the identification of a further 11 barriers. Thus, 27 barriers closely related to China's context were deemed eligible for further analysis.

As shown in Table 2, we categorized the identified barriers into technological, economic, social, environmental, organizational and supply chain dimensions. Several steps were followed in this categorization. First, we acquired a broad understanding by examining previous relevant literature. Second, we adopted GT as a theoretical lens requiring to categorize the barriers by considering macro-level environments, meso-level supply chains and micro-level organizations. Finally, we conducted structured interviews to further refine the results.

4.2 | Barrier prioritization using GFAHP

To analyse barriers to adopting I4.0 to achieve AFSC sustainability, we implemented a six-step GFAHP.

Step 1: Define and structure the problem to be analysed. This step involved structuring the problem hierarchically, including goals, dimensions and barriers. Our goal was to prioritize our barriers. We categorized the 27 identified barriers into seven dimensions (see Table 2) and used them as inputs into further analysis.

Step 2: *Define fuzzy numbers for performing pair-wise comparisons*. In the traditional AHP algorithm, decision makers are asked to conduct pair-wise comparisons of alternatives and score them using a nine-level relative importance scale. The higher the number, the greater the pairs differ in importance (see

TABLE 2 Barriers to I4.0 adoption for AFSC sustainability in China.

Dimension	Barrier	Description	References
Technological barriers (T)	Imported technology cannot be adapted to China's agricultural environment (T1)	The soil in China differs from that in the European Union. The soil does not harden	Expert's contribution
	Low compatibility of I4.0 technologies with existing agricultural equipment (T2)	Agricultural mechanization has been achieved. However, the connection between information technology and machine operating systems is not very good	Dwivedi and Paul (2022); Trevisan et al. (2023)
	Low maturity of integrated I4.0 technologies (T3)	The existing technical equipment is integrated, and the maturity of technical equipment needs to be improved	Raj et al. (2020); Annosi et al. (2021)
	Lack of unified technical standard (T4)	There is no technical standard for applying I4.0 technologies	Kumar, Singh et al. (2021); Govindan (2022)
	Model/interface to control technologies needs further improvements (T5)	What kind of model to use to achieve precise control, and what kind of control is more accurate; model equipment must be integrated	Expert's contribution
	Unreliability of the technology (T6)	The facilities are not particularly reliable, and the data are occasionally very inaccurate	Govindan (2022); Taddei et al. (2024)
	Poor internet connection in rural areas (T7)	Another restriction for deploying I4.0 technologies is poor internet connection in rural areas	Raj et al. (2020); Cui et al. (2021)
Economic barriers (E)	High cost of using intelligent agricultural equipment (E1)	In the process of dissemination, the cost of technical equipment is too high. This is because the application has just begun, and the large-scale production of technical equipment has not yet formulated a scale effect	Raj et al. (2020); Dwivedi et al. (2022)
	High cost of maintaining intelligent agricultural equipment (E2)	The maintenance cost is relatively high for large equipment such as pumping stations and sediment filtration	Kumar, Singh et al. (2021)
	Long payback period (E3)	Farmers cannot see the short-term benefits of applying these I4.0 technologies	Mangla et al. (2022)
Social barriers (S)	Lack of awareness of applications of I4.0 technologies (S1)	The incomplete basic data turned out to be a cognitive problem	Dwivedi and Paul (2022)
	Ageing workforce (S2)	For existing farmers, the general age is above 45 years old, and most are around 55 years old	Kouhizadeh et al. (2021)
	Lack of skills to maintain and repair equipment (S3)	Inadequate maintenance of equipment	Raj et al. (2020); Yilmaz et al. (2022)
	Low knowledge retention by farmers (S4)	Farmers are low in knowledge	Karadayi-Usta (2020); Cui et al. (2021)
	Low technology/knowledge acceptance level (S5)	Industry practitioners are reluctant to use I4.0 technologies	Dwivedi and Paul (2022); Govindan (2022)
	Psychological resistance to using I4.0 technologies (S6)	In the process of applying this technical equipment, there is also a psychological obstacle	Majumdar, Garg, and Jain (2021); Taddei et al. (2024)
Environmental barriers (N)	Acquisition of intelligent agricultural equipment subsidies based on *guanxi* (N1)	The support is not inclusive; it is based on relationships	Expert's contribution
	Insufficient government incentives (N2)	Governments provide financial incentives to support technology deployment, but it is not enough	Ozkan-Ozen et al. (2020); Dwivedi and Paul (2022)
	Reluctance to share knowledge to avoid competition (N3)	For example, the farmer found a good planning model, but he was unwilling to spread it. In fact, avoiding competition	Annosi et al. (2021)
	Problems with the government subsidy model (N4)	At this stage, subsidies should not be given to farmers. Let us see if we can subsidize manufacturers	Expert's contribution
Organizational barriers (O)	Lack of experience to manage equipment (O1)	There is also no mature management experience in the maintenance and use of equipment	Trevisan et al. (2023); Taddei et al. (2024)
	Lack of top management support (O2)	This is the beginning of the implementation of these technologies; therefore, managers do not believe that digital technology can replace the human brain	Shuvabrata et al. (2020); Taddei et al. (2024)

TABLE 2 (Continued)

Dimension	Barrier	Description	References
	Lack of digital management culture (O3)	There is no concept of digital technology, and there is no culture that relies on digital technology management	Abdul-Hamid et al. (2020)
Supply chain barriers (C)	Lack of non-profit knowledge brokers to transfer knowledge and skills (C1)	The third level is called technical services or intermediaries, rather than directly targeting farmers from manufacturers or research institutions.	Expert's contribution
	Applying I4.0 technologies will increase the cost of terminal logistics (C2)	When the IoT or blockchain technology is deployed in rural areas, the cost of terminal logistics is too high	Expert's contribution
	Knowledge boundaries impeding I4.0 knowledge mobilization (C3)	But whether farmers can understand I4.0 technologies or apply these technologies is another concept	Dwivedi et al. (2022)
	Lack of collaboration with research institutes (C4)	Farmers do not want to collaborate with universities and research institutes to update their skills and knowledge	Karadayi-Usta (2020); Majumdar, Garg, and Jain (2021)

TABLE 3 Scale of relative importance versus fuzzy scale of relative importance.

	Scale of relative importance	Fuzzy scale of relative importance
Equal importance	1	(1,1,1)
Moderate importance	3	(2,3,4)
Strong importance	5	(4,5,6)
Very strong importance	7	(6,7,8)
Extremely strong importance	9	(8,9,9)
Intermediate values	2,4,6,8	(1,2,3), (3,4,5), (5,6,7), (7,8,9)
Values for inverse comparison	1/3, 1/5, 1/7, 1/9	(1/3,1/2,1/1) … (1/9,1/9,1/8)

Source: Modified from Jurevičienė and Skvarciany (2016, p. 166).

Table 3). Integrating fuzzy set theory optimizes the AHP algorithm (Saaty & Tran, 2010), so a fuzzification process is used to convert crisp values into fuzzy values to regulate the degree of membership.

In the fuzzy AHP algorithm, each alternative in the decision-making pairwise matrix is no longer a single number, but is replaced with three numbers to describe the relationship between two alternatives. For example, (1, 2, 3) represent a relationship between equal importance (1) and moderate importance (3). The relationship is a fuzzy range rather than a definite value. This fuzzification helps simplify decision makers' inputs, especially if they have little decision-making experience. Table 3 shows the scale of relative importance and the fuzzy scale of relative importance.

Step 3: Invite experts to score dimensions, construct fuzzy pairwise matrices and calculate each expert's weighting for each dimension. Three Chinese agri-food professionals who had collaborated with the agri-food industry for more than 30 years and had expertise in agricultural equipment and AFSC management were asked to score the dimensions using the fuzzy scale of relative importance (see Appendix B.1). We selected three agri-food professionals to score the dimensions for several reasons. First, the 10 experts previously consulted (see Section 4.1) had diverse expertise, but only those with both expertise in AFSC management and agricultural equipment and decision-making experience were included in our detailed analysis. Second, not all experts were interested in scoring the dimensions. Third, people tend to prefer groups of two or three members to solve decision-making problems. A group of this size promotes greater uniqueness, prevents process loss and coordination problems and is easier to manage than groups with more than six members (Li & Liao, 2023). The experts' scores were plugged into pairwise matrices. For example, M^n represents the pairwise matrix after scoring by expert n. For the element m_{ij}^n in matrix M^n, if $i=j$, then $m_{ij}^n=(1,1,1)$.

$$\mathrm{M}^{\mathrm{n}}=\left\{\mathrm{m}_{\mathrm{ij}}^{\mathrm{n}}\right\},\mathrm{i}=1,2\cdots6,\mathrm{j}=1,2\cdots6$$

$$\mathrm{m}_{\mathrm{ij}}^{\mathrm{n}}=\left(\mathrm{a}^{1},\mathrm{a}^{2},\mathrm{a}^{13}\right),\mathrm{m}_{\mathrm{ij}}^{\mathrm{n}}=\left\{\mathrm{m}_{\mathrm{ij}}^{\mathrm{n}}\right\}^{-1}$$

We then calculated the weighting of each dimension based on the expert's matrix. First, it was necessary to calculate the fuzzy geometric mean value, Si for each expert based on the following equation:

$$S_i^n=\sum\nolimits_{j=1}^{n}m_{ij}^n\left[\sum\nolimits_{i=1}^{n}\sum\nolimits_{j=1}^{n}m_{ij}^n\right]^{-1},\text{where } S_i^n=\{s_i\},s_i=(s_1,s_2,s_3)$$

Second, we performed a de-fuzzification process on Si to convert it into a one-dimensional vector, $\overline{S_i^n}$:

$$\text{where} \quad \overline{s_i} = \frac{s_1 + 2 * s_2 + s_3}{4}$$

Third, we normalized S*i* to obtain the weighting of each dimension for each expert based on the following equation:

$$W^n = \frac{\overline{S_i}}{\sum_{i=1}^{n} \overline{S_i}}$$

Fourth, we calculated the largest eigenvalue of matrix $\lambda_{max} = \frac{\sum (AW)_i}{NW_i}$. Similarly, we initially de-fuzzified each expert's fuzzy pairwise matrix, using the same process as for the defuzzification calculation method for vector $\overline{S_i^n}$. We then labelled the matrix M^n, where *n* represents the number of dimensions. In this study with six dimensions of barriers, $n = 6$.

Finally, we checked the consistency of experts' opinions and controlled the results of this method. The consistency ratio (CR) for each expert's matrix signifies the uniformity of the expert's judgements. Judgements are consistent when CR ≤ 0.10, indicating an acceptable pairwise comparison matrix (Saaty, 1996). To calculate the CR, we needed to obtain the average random consistency index (RI) (see Appendix B.2), which relates only to the order *n* of the matrix. In this case, the RI is 1.24 based on our six dimensions (n = 6). The values of the consistency index (CI) and CR are used in consistency analysis based on the following formulae:

$$CI = \frac{(\lambda_{max} - n)}{(n-1)}, CR = \frac{CI}{RI}.$$

Thus, we obtained the weighting of dimension WD_i^n for each expert (see Appendix B.3) and the CR for dimension calculation C_D^n for each expert's decision, where *i* represents the six dimensions from 1 to 6, and *n* represents the codes for different experts. Our consistency testing results showed that the value of CR was less than or equal to 0.10, indicating consistency between the three agri-food professionals.

Step 4: *Invite experts to score barriers, construct fuzzy pairwise matrices and calculate the weighting of each barrier by each expert*. The same agri-food professionals were asked to conduct pairwise comparisons of the barriers within each dimension to obtain fuzzy pairwise matrices (see Appendix B.4). We then repeated the same calculation process in Step 3 to obtain the weighting of each barrier by each expert and conducted consistency testing (see Appendix B.5). The test results showed consistency between the three experts, as the CR values were all less than or equal to 0.10. Finally, we uniformly marked the barriers' weightings as WB_i^n, where *i* represents the barrier and *n* represents the experts' coding. For example, the weighting of technological barriers is represented by W_T^n. Similarly, we labelled the CR value for each expert as C_i^n.

Step 5: *Calculate the weightings of agri-food professionals*. The three agri-food professionals were given decision weightings to compare and judge their logic (see Appendix B.6). Thus, it was necessary to calculate the average CR for each agri-food professional as a basis for measuring the logic:

$$C_R^n = \frac{C_T^n + C_E^n + C_S^n + C_N^n + C_O^n + C_C^n + C_D^n}{7}$$

To assess the logic, we introduced variable P^n to calculate the agri-food professional's weighting, calculated as follows:

$$P_n = \frac{1}{1 + aC_R^n}, a > 0, n = 1, 2......m$$

In the formula, constant *a* has a value of 10, and *n* represents the code given by the agri-food professional. P_n^* denotes the weighting by the decision maker, calculated as follows:

$$P_n^* = \frac{P_n}{\sum_{n=1}^{m} P_n}$$

Step 6: *Calculate the final weightings and prioritize dimensions and barriers after collective decision making*. In Steps 3 and 4, we calculated the weighting of each dimension and each barrier by each expert. These results were used as inputs to obtain the final weightings of dimensions and barriers after the three experts' collective decision making, using the following formulae:

$$WD_i^{Group} = \sum_{n=1}^{3} P_n^* * WD_i^n$$

$$WB_i^{Group} = \sum_{n=1}^{3} P_n^* * WD_i^n * WB_i^n$$

Table 4 presents the final ranking of dimensions and barriers to I4.0 adoption to achieve AFSC sustainability in China. This shows that the environmental dimension is ranked highest, followed by the supply chain, social, technological, organizational and economic dimensions.

The environmental category of barriers (N) is ranked first in the priority list. This dimension contains four barriers: acquisition of intelligent agricultural equipment subsidies based on *guanxi* (N1), insufficient government incentives (N2), reluctance to share knowledge to avoid competition (N3), and problems with the government subsidy model (N4). Among these, N1 is ranked first, followed by N4, N3 and N2. Interestingly, this result reflects China's hierarchical cultural value orientation, which legitimizes unequal distribution of power, roles and resources (Schwartz, 2006) and values social power, authority and wealth. Thus, AFSC practitioners unsurprisingly seek to make connections with key bureaucrats to acquire more subsidies. As one agri-food

TABLE 4 Final ranking of dimensions and barriers after collective decision-making.

Dimension of barriers	Relative weighting	Relative rank	Specific barriers	Relative weighting	Relative rank	Global weighting	Global rank
Technological (T)	0.0653553	4	T1	0.034951323	6	0.00186157	24
			T2	0.322010825	1	0.01655718	3
			T3	0.270917941	2	0.01353173	5
			T4	0.198775914	3	0.0106222	10
			T5	0.026476159	7	0.00135111	25
			T6	0.097539917	4	0.00497825	14
			T7	0.049327921	5	0.00244188	21
Economic (E)	0.03041151	6	E1	0.153687623	3	0.00275249	19
			E2	0.284488046	2	0.0050411	13
			E3	0.561824328	1	0.01119852	9
Social (S)	0.20615551	3	S1	0.120846004	3	0.00429421	16
			S2	0.100022951	4	0.00373579	17
			S3	0.066710933	5	0.00242978	22
			S4	0.360215605	1	0.0134605	6
			S5	0.323392166	2	0.01146213	7
			S6	0.028812342	6	0.00105492	27
Environmental (N)	0.41955704	1	N1	0.560260765	1	0.02741982	2
			N2	0.053334943	4	0.0024492	20
			N3	0.06096297	3	0.00311294	18
			N4	0.325441322	2	0.0154933	4
Organizational (O)	0.05034466	5	O1	0.605292781	1	0.00540615	12
			O2	0.21866262	2	0.00210817	23
			O3	0.176044592	3	0.00123283	26
Supply chain (C)	0.22817597	2	C1	0.108888914	3	0.00596519	11
			C2	0.660108789	1	0.04194063	1
			C3	0.165026715	2	0.01125595	8
			C4	0.065975578	4	0.00434132	15

professional stated, 'The government provides subsidies for farmers to purchase intelligent agricultural equipment. However, this kind of support is not universal, but based on guanxi.' Problems with the government subsidy model (N4) is ranked second in this category. This is because the government currently gives subsidies to the purchasers rather than manufacturers of intelligent agricultural facilities. One of our agri-food professionals said: 'At this stage, it is better that we can subsidize manufacturers rather than farmers because we are at the initial stage of applying intelligent agricultural equipment. We should subsidize agricultural technology and equipment.' The other two barriers in this category, reluctance to share knowledge to avoid competition (N3) and insufficient government incentives (N2), are prioritized third and fourth, respectively. The former relates to China's hierarchical cultural environment, in which people reject new realities and view competition as good: 'People are worried that others will learn from them after they have done well, so they keep it to themselves. For example, he discovered a good planting model, but he was unwilling to spread it.' The latter refers to current incentives not attracting sufficient AFSC practitioners, for example because equipment prices are too high for most AFSC practitioners, although they may obtain subsidies.

The supply chain dimension (C) occupies second place in the priority list. Among the four barriers in this category, the increased cost of terminal logistics (C2) has the highest priority. One of our agri-food professionals suggested 'When the IoT or blockchain is introduced to rural areas, the logistics cost at the end will be too high. For example, for several major logistics companies in China, farmers produced strawberries at ¥5, but maybe sold to final consumers for ¥25.' Knowledge boundaries impeding I4.0 knowledge mobilization (C3) and lack of non-profit knowledge brokers to transfer knowledge and skills (C4) are ranked second and third in the priority list. Lack of knowledge of I4.0 is frequently mentioned by scholars as impeding I4.0 adoption (Stentoft et al., 2021), but their descriptions lack detail. Our findings provide answers to 'why' lack of I4.0 knowledge occurs. First, an ageing workforce in the agri-food industry and China's hierarchical cultural environment result in psychological resistance to learning and sharing knowledge relating to I4.0. Second, it is difficult to change farmers' view through simple knowledge-sharing channels, such as lectures and theoretical training. Third, non-profit technical service organizations to coordinate knowledge-sharing activities among universities, research institutes, AFSC practitioners and manufacturers are lacking. Their role is critical, particularly when conflicts arise. One of our agri-food professionals suggested: 'There should be a level of agricultural technology promotion. They have direct contact with our universities, manufacturers and research institutions.' Lack of collaboration with research institutes (C4) is last in the list of priorities.

The social dimension of barriers (S) is third in the priority list. These barriers comprise lack of awareness of I4.0 technology applications (S1), an ageing workforce (S2), lack of skills to maintain and repair equipment (S3), low knowledge retention by farmers (S4), low technology/knowledge acceptance (S5) and psychological resistance to using I4.0 technologies (S6). Among these, S4 is highest in priority, and S6 lowest. These barriers relate closely to the age and knowledge structure of AFSC practitioners. According to the National Bureau of Statistics of China (2022), only 13.6% of those employed in agriculture, forestry, animal husbandry and fisheries are under the age of 35 years. Our discussions with agri-food professionals elicited similar opinions: 'The average age of existing farmers is more than 45 with most of them around 55 years old. They are relatively high in age and low in knowledge structure. This results in them not being good at model application and equipment maintenance.' Moreover, experienced farmers are used to managing crops, so when the results of automatic and manual management diverge, they prefer to cultivate crops based on their own experience. This explains why AFSC practitioners do not trust I4.0 technologies and are resistant to change.

The technological dimension (T) is ranked fourth in importance. In this category, the top three barriers are low compatibility of I4.0 technologies with existing agricultural equipment (T2), low maturity of integrated I4.0 technologies (T3) and lack of a unified technical standard (T4). I4.0 applications are advanced, intelligent digital technologies that can be used to improve manufacturing and production processes (Mantravadi et al., 2023). Therefore, supporting facilities, such as high-speed internet in rural areas, pesticides for water and fertilizer integration systems and high-quality farmland for automatic tractors, are critical to I4.0 adoption. This was confirmed by our agri-food professionals: 'I4.0 are cutting-edge technologies. However, matching these technologies requires a process. If the implementation path cannot be matched, it is not worth using these technologies.' Furthermore, the quality of I4.0 technologies is a problem for AFSC practitioners, with issues such as low reliability and inaccurate data generation causing distrust. The remaining four barriers in this category are unreliability of technology (T6), poor internet connections in rural areas (T7), imported technology that cannot be adapted to China's agricultural environment (T1) and the model/interface to control technologies needing further improvement (T5). Some intelligent agricultural technologies, including automatic ventilation cooling systems and automatic tractors imported from countries such as the Netherlands, Japan and Israel, cannot easily be adapted to China's natural environment owing to huge differences in climate, soil and light. As one agri-food professional noted: 'The soil in China is different from that in the European Union (EU). It hardens with difficulty and will change greatly after watering. This situation means that automatic tractors imported from EU cannot be applied.'

The organizational dimension (O) occupies the fifth place in the priority list. Among the three barriers in this category, lack of experience to manage equipment (O1) is prioritized the highest for several reasons. First, intelligent agricultural facilities are composed of many subsystems. For example, intelligent greenhouses include environmental controls, automatic drip irrigation and water and fertilizer integration systems. The complexity of intelligent agricultural facilities makes them difficult to manage. Second, as stated earlier, most intelligent agricultural facilities in China are currently imported from other countries such as the Netherlands. The geographical distance between China and the Netherlands raises barriers to knowledge mobilization, technical staff mobility and importation of technical components. Third, the novelty of intelligent agricultural facilities means that few people have experience of managing them, so lack of experience to manage equipment (O1) is unsurprisingly given top priority. Lack of top management support (O2) is ranked second. This is because China is at the initial stage of applying intelligent agricultural technologies, so managers do not trust them. As one of our agri-food professionals stated: 'Implementing intelligent technology means letting external brains replace human brains. In large manufacturing factories, managers believe in these technologies. However, in most agri-food organizations, managers do not believe in them.' Finally, lack of a digital management culture (O3) is ranked last in this dimension. One agri-food professional mentioned a cognitive gap between managers' knowledge and reality: 'There is no concept of digital technology and no culture that relies on digital technology management.'

The economic dimension (E) is last in the priority list. Of the three barriers in this category, a long payback period (E3) is ranked first, followed by the high cost of maintaining intelligent agricultural equipment (E2) and the high cost of using it (E1). These barriers result from several factors. First, China is at the initial stage of applying intelligent agricultural facilities, so production has not yet reached scale. Second, family farms in China have an average of 134 acres of farmland, compared with 445 acres in the United States, making Chinese family farmers less willing to use intelligent agricultural facilities. The situation is even worse for farmers with only two or three acres of farmland. One of our agri-food professionals stated: 'Many farmers in China only have three acres of farmland and their yearly income is ¥2,000. An increase of 20% per acre will only increase more than ¥1,000, which will have little impact on their family income. The situation is different when a farmer has more than 200 acres of farmland. They may agree with using intelligent agricultural facilities.'

5 | DISCUSSION AND CONTRIBUTIONS

In this section, we compare our findings with those of previous studies and explain our unique contributions to knowledge and managerial practices.

5.1 | Knowledge and theoretical contributions

Our results produce novel insights into barriers to I4.0 adoption for AFSC sustainability that differ from those of most existing studies. For example, Kumar, Brar et al. (2022) prioritize five categories of I4.0 adoption barriers relating to the Indian manufacturing industry, with economic and technological barriers ranked first and second. Similarly, other studies of I4.0 adoption barriers in various contexts (Kamble et al., 2018; Majumdar, Sinha, & Govindan, 2021; Senna et al., 2022), suggest that economic and technological barriers should be given critical attention. However, in our study, environmental and supply chain categories of barriers are prioritized for several reasons. First, the Chinese government has been promoting modern agriculture since 2012; therefore, support such as payments based on planted area and minimum purchasing prices for agricultural products have increased consistently since 2014 (Li et al., 2023). Between 2019 and 2021, three aspects of agricultural activity attracted the greatest financial support (12.2% of total support): public stockholding, development and maintenance of infrastructure, and agricultural knowledge and innovation systems. This is also why the technological and economic dimensions are given lower priority. Second, China's hierarchical cultural value orientation means that bureaucrats at various levels of government have discretional power to allocate resources (Bian, 2018). Therefore, personal connections (*guanxi*) with key government officers are necessary to gain access to controlled resources such as subsidies. This results in environmental barriers being given the highest priority. Third, China's AFSCs are characteristically small-scale and highly decentralized. The current production model focuses on production and pays little attention to other links in AFSCs. Thus, the supply chain dimension of barriers occupies second place in the priority list.

Our global prioritization of barriers also produces a novel ranking, with I4.0 increasing the cost of terminal logistics (C2) ranked first, acquisition of intelligent agricultural equipment subsidies based on *guanxi* (N1) second and low compatibility of I4.0 technologies with existing agricultural equipment (T2) third in the priority list. In similar studies, Bajpai and Misra (2023) prioritize 14 barriers to implementing digitalization in the Indian construction industry and indicate that lack of regulation and standardization is the key barrier; and Ada et al.'s (2022) study of barriers to CE for agricultural cooperatives in the era of I4.0 suggests that insufficient implementation of CE laws is the most important barrier. However, in our study, regulation is ranked 10th among the 27 identified barriers. Deepu and Ravi (2023) find that lack of awareness of digitalization is particularly relevant to tackling barriers to supply chain digitalization, whereas in our study lack of awareness is ranked 16th among the 27 barriers. Khan et al.'s (2023) investigation of barriers to digital technology adoption in supply chains reveals the primary influence of lack of information sharing and trust management issues. In contrast, our study suggests that the high-cost and low compatibility of I4.0 technologies and the difficulty of acquiring subsidies are primary barriers to agricultural I4.0 adoption.

Among the 27 barriers identified in this study (see Table 2), several are new to AFSC sustainability. Among Kumar, Raut et al. (2021) 11 barriers to I4.0 adoption for AFSC sustainability, lack of government support is the top priority, followed by lack of awareness and lack of effective policy and protocol. In Luthra and Mangla's (2018) ranking of 18 I4.0 adoption barriers, the top three are lack of a data-sharing framework, lack of government support and financial constraints. Shang et al. (2022) reveal 13 I4.0 adoption barriers, and prioritize deficient knowledge and lack of awareness of the potential benefits of I4.0. Finally, Chhabra and Singh (2022), who identify 16 I4.0 adoption barriers, suggest that lack of top management support, employees' resistance to change and lack of a consistent approach to I4.0 technologies should be given critical attention. Our study presents a different understanding because we link the agri-food industry closely with China's social, political, economic and cultural environments. Thus, we identify six I4.0 adoption barriers seldom mentioned by other scholars: acquisition of intelligent agricultural equipment subsidies based on *guanxi* (N1), problems with the government subsidy model (N4), I4.0 technologies increasing the cost of terminal logistics (C2), inability to adapt imported I4.0 agricultural technology to China's agricultural environment (T1), improvements required to the model/interface to control I4.0 technologies (T5) and lack of non-profit knowledge brokers to transfer knowledge and skills (C1).

GT has seldom been used to analyse I4.0 adoption barriers to achieve AFSC sustainability. Scholars have applied various other theories. For example, Chauhan et al. (2021) adopt CT and RBV to understand the impact of extrinsic and intrinsic barriers to I4.0 adoption on I4.0 practices, and indicate that both types of barrier impact negatively on digitalization. Senna et al. (2022) utilize the technology–organization–environment framework to categorize barriers to the adoption of I4.0 technologies, and Masood and Sonntag (2020) apply the technology acceptance model to understand I4.0 adoption challenges. In contrast, we take an initial step in applying GT to analyse I4.0 adoption barriers and understand this issue from the macro-, meso- and micro-levels of environments, supply chains and organizations. We also contribute to theory by identifying several barriers arising from China's unique environments, including acquisition of intelligent agricultural equipment subsidies based on *guanxi* (N1). Utilizing GT enables us to identify a wider range of aspects influencing I4.0 adoption than could be obtained using other theories. For example, Senna et al. (2022) identify I4.0 adoption barriers from technological, organizational and environmental perspectives, but do not consider cultural and social perspectives. Thus, our study contributes to GT by linking China's cultural, economic and social environments with I4.0 adoption barriers.

5.2 | Managerial implications

Our study has several useful managerial implications for policymakers, research institutes/universities and AFSC practitioners in China.

First, our agri-food professionals criticized the existing government subsidy model for being *guanxi* and purchaser based. Our results rank acquisition of intelligent agricultural equipment subsidies based on *guanxi* (N1) first in the environmental category and second overall, while problems with the government subsidy model (N4) is ranked second and fourth, respectively (see Table 4). *Guanxi* is prevalent in China's hierarchical cultural environment, so is difficult to avoid. To alleviate this situation, we suggest that government should provide subsidies to manufacturers based on the quantity of intelligent agricultural facilities manufactured and sold, rather than providing subsidies to purchasers. However, subsidies should only be given to leading enterprises that have wide links with farmers and master cutting-edge agricultural technologies. The situation might also be alleviated if the government were to publish detailed subsidy data on its official website to enable public scrutiny.

The supply chain barrier category is ranked second out of the six categories. Overall, the individual barriers of applying I4.0 technologies increasing the cost of terminal logistics (C2), knowledge boundaries impeding I4.0 knowledge mobilization (C3) and lack of non-profit knowledge brokers to transfer knowledge and skills (C1) are ranked first, eighth and eleventh, respectively. This is because Chinese AFSC practitioners rely on simple knowledge-sharing channels such as lectures to obtain knowledge, while professional knowledge brokers who might coordinate relationships between research institutes, universities, manufacturers and AFSC practitioners are lacking. Thus, we suggest the establishment of a non-profit knowledge dissemination organization, focusing specifically on providing practical training sessions. Such an organization will be particularly critical when conflicts arise between manufacturers and AFSC practitioners. To boost AFSC practitioners' interest in attending practical training sessions, vouchers or gifts (e.g., agrichemicals and pesticides) might be provided, while ensuring delivery of knowledge that AFSC practitioners really care about.

The social dimension of barriers ranked third among the six categories, and the individual barriers of low knowledge retention by farmers (S4) and low technology/knowledge acceptance levels (S5) are ranked sixth and seventh overall. The Chinese government is currently deploying large-scale education and training to foster its next generation of farmers. Data show that China has trained five million high-quality farmers during the 13th Five-Year Plan (State Council, 2020). However, the programme covers only farmers, rather than all AFSC practitioners willing to learn I4.0 knowledge and skills. Thus, we suggest that the Chinese government should expand enrolment to cover all AFSC practitioners to enhance their I4.0 knowledge and technology acceptance levels.

Technological category of barriers ranked fourth. Two notable barriers in this category are low compatibility of I4.0 technologies with existing agricultural equipment (T2) and low maturity of integrated I4.0 technologies (T3). These barriers have emerged because basic data for modelling is incomplete, existing data models and agricultural equipment are not well integrated and relevant standards are lacking. Thus, several adaptation routes are suggested. First, agricultural parameters should be modelled to fit various soil, light, carbon dioxide concentration, pH, climate and moisture conditions. Second, simplified agricultural equipment software interfaces might be implemented, for example not exceeding three levels and with voice control. Third, country-wide agricultural equipment technical standards should be established, especially for equipment integrated into I4.0 technologies. Finally, the government should continue to invest in rural areas to provide supporting facilities for intelligent agricultural equipment, such as high-speed internet and pesticides for water and fertilizer integration systems.

With regard to organizational barriers, lack of experience to manage equipment (O1), lack of top management support (O2) and lack of digital management culture (O3) are ranked 12th, 23rd and 26th overall. With a hierarchical cultural value orientation, organizational management teams play a critical role in fostering a digital management culture and accelerating digital transformation. Thus, they must create a narrative for change and inspire the workforce to embrace digital transformation.

Finally, one feasible way to tackle economic barriers such as the high cost of using intelligent agricultural equipment (E1), the high cost of maintaining intelligent agricultural equipment (E2) and long payback periods (E3) is to scale up the digital agricultural industry scale to reduce costs, such as forming industrial clusters focusing on manufacturing intelligent agricultural equipment.

6 | CONCLUSION, LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

In the face of climate change and a global population explosion, AFSCs must be operated more efficiently, effectively and sustainably. I4.0 technologies may be a crucial facilitator, but various barriers hamper their adoption. Therefore, using GT, we explore the intersection of I4.0 technologies, AFSC sustainability and barriers. We identified 27 barriers to I4.0 adoption f or AFSC sustainability by reviewing existing literature and consulting 10 Chinese experts. We then adopted a GFAHP approach to prioritize the barriers. Our results differ from those of existing studies and thus enrich knowledge. For example, we identify six new barriers closely linked with China's cultural, social and economic environments, including acquisition of intelligent agricultural equipment subsidies based on *guanxi*, problems with the government subsidy model, I4.0 technologies increasing the cost of terminal logistics, inability to adapt imported I4.0 agricultural technology to China's agricultural environment, improvements required to the model/interface to control I4.0 technologies, and lack of non-profit knowledge brokers to transfer knowledge and skills. Our dimension prioritization is also novel in ranking the environmental and supply chain dimensions first and second out of six dimensions, rather than the technological and economic dimensions frequently mentioned in previous studies. In our overall prioritization of barriers, the top three are I4.0 technologies increasing the cost of terminal logistics, acquisition of intelligent agricultural equipment subsidies based on *guanxi* and I4.0 technologies being incompatible with existing agricultural equipment. Our results complement existing studies by identifying new barriers and providing a new perspective for understanding the relative importance of the 27 barriers. In terms of theoretical contributions, this study is the first to apply GT to understand barriers to adopting I4.0 to achieve AFSC sustainability.

6.1 | Limitations and future research directions

Despite adopting a rigorous research methodology, our study has some limitations.

First, our study focuses on China and therefore has generalizability issues. China has a unique hierarchical cultural value orientation, and we conclude that several barriers are closely connected with this cultural environment. Future studies might evaluate barriers and their prioritization in countries with different cultural value orientations, including embeddedness, harmony, egalitarianism, intellectual autonomy, affective autonomy and mastery (Schwartz, 2006).

Second, we adopted a GFAHP approach to prioritize the I4.0 adoption barriers. Unlike other studies, we averaged and normalized the CR value of each decision maker to comprehensively evaluate their logic, and used these values as criteria to evaluate the proportion of decision makers in the decision-making problem. However, every approach has limitations, including GFAHP. Future research might adopt different MCDM approaches such as the technique for order preference by similarity to ideal solution, when evaluating decision-making problems, in order to balance the limitations of each approach.

Third, our SLR and expert consultations revealed 27 barriers across six dimensions. Our study presents a detailed understanding of barriers to I4.0 adoption for AFSC sustainability, but is far from conclusive. This is because our SLR only considered papers published in high-quality journals, and we only involved a few experts in the consultation process. Thus, future research might involve more experienced agricultural experts from diverse backgrounds, and consider other types of publications such as conference papers, book chapters and organization reports to identify relevant barriers.

Finally, in this study, we obtained the opinions of three experts for our GFAHP. Considering the opinions of a range of decision makers to prioritize barriers has merit for tackling decision-making problems. To obtain more precise ranking, future studies might involve a larger number of decision makers. Involving more than 20 experts in a decision-making problem is normally considered to be large-scale group decision making (Ming et al. 2020).

CONFLICT OF INTEREST STATEMENT

No relevant financial or non-financial competing interests to report.

DATA AVAILABILITY STATEMENT

The authors confirm that the data supporting the findings of this study are available within the article [and/or] its supplementary materials.

ORCID

Guoqing Zhao https://orcid.org/0009-0003-9537-9016
Denis Dennehy https://orcid.org/0000-0001-9931-762X

REFERENCES

Abbate, S., Centobelli, P., & Cerchione, R. (2023). The digital and sustainable transition of the agri-food sector. *Technological Forecasting and Social Change*, *187*, 122222. https://doi.org/10.1016/j.techfore.2022.122222

Abdul-Hamid, A.-Q., Ali, M. H., Tseng, M.-L., Lan, S., & Kumar, M. (2020). Impeding challenges on I4.0 in circular economy: Palm oil industry in Malaysia. *Computers & Operations Research*, *123*, 105052. https://doi.org/10.1016/j.cor.2020.105052

Ada, E., Sagnak, M., Uzel, R. A., & Balcioglu, I. (2022). Analysis of barriers to circularity for agricultural cooperatives in the digitalization era. *International Journal of Productivity and Performance*, *71*(3), 932–951. https://doi.org/10.1108/IJPPM-12-2020-0689

Agnusdei, G. P., & Coluccia, B. (2022). Sustainable Agri-food supply chains: Bibliometric, network and content analyzes. *Science of the Total Environment*, *824*, 153704. https://doi.org/10.1016/j.scitotenv.2022.153704

Ahi, P., & Searcy, C. (2013). A comparative literature analysis of definitions for green and sustainable supply chain management. *Journal of Cleaner Production*, *52*, 329–341. https://doi.org/10.1016/j.jclepro.2013.02.018

Akcayir, M., & Akcayir, G. (2017). Advantages and challenges associated with augmented reality for education: A systematic review of the literature. *Educational Research Review*, *20*, 1–11. https://doi.org/10.1016/j.edurev.2016.11.002

Aly, B. A., Low, T., Long, D., Baillie, C., & Brett, P. (2023). Robotics and sensing technologies in red meat processing: A review. *Trends in Food Science & Technology*, *137*, 142–155. https://doi.org/10.1016/j.tifs.2023.05.015

Annosi, M. C., Brunetta, F., Bimbo, F., & Kostoula, M. (2021). Digitalization within food supply chains to prevent food waste. Drivers, barriers and collaboration practices. *Industrial Marketing Management*, *93*, 208–220. https://doi.org/10.1016/j.indmarman.2021.01.005

Awan, U., Golgeci, I., Makhmadshoev, D., & Mishra, N. (2023). Industry 4.0 and circular economy in an era of global value chains: What have we learned and what is still to be explored? *Journal of Cleaner Production*, *371*, 133621. https://doi.org/10.1016/j.jclepro.2022.133621

Awan, U., Sroufe, R., & Shahbaz, M. (2021). Industry 4.0 and the circular economy: A literature review and recommendations for future research. *Business Strategy and the Environment*, *30*(4), 2038–2060. https://doi.org/10.1002/bse.2731

Bajpai, A., & Misra, S. C. (2022). Barriers to implementing digitalization in the Indian construction industry. *International Journal of Quality & Reliability Management*, *39*(10), 2438–2464. https://doi.org/10.1108/IJQRM-09-2020-0318

Bian, Y. (2018). The prevalence and the increasing significance of Guanxi. *The China Quarterly*, *235*, 597–621. https://doi.org/10.1017/S0305741018000541

Birkel, H., & Muller, J. M. (2021). Potentials of I4.0 for supply chain management within the triple bottom line of sustainability—A systematic literature review. *Journal of Cleaner Production*, *289*, 125612. https://doi.org/10.1016/j.jclepro.2020.125612

Bouzembrak, Y., Kluche, M., Gavai, A., & Marvin, H. J. P. (2019). Internet of things in food safety: Literature review and a bibliometric analysis. *Trends in Food Science & Technology*, *94*, 54–64. https://doi.org/10.1016/j.tifs.2019.11.002

CABS. 2021. *Academic journal guide 2021*. Available at: https://charteredabs.org/academic-journal-guide-2021/ [Accessed: 06/06/2023].

Canas, H., Mula, J., Diaz-Madronero, M., & Campuzano-Bolarin, F. (2021). Implementing industry 4.0 principles. *Computers & Industrial Engineering*, *158*, 107379. https://doi.org/10.1016/j.cie.2021.107379

Cappelletti, F., Papetti, A., Rossi, M., & Germani, M. (2022). Smart strategies for household food waste management. *Procedia Computer Science*, *200*, 887–895. https://doi.org/10.1016/j.procs.2022.01.286

Carter, C. R., & Rogers, D. S. (2008). A framework of sustainable supply chain management: Moving toward new theory. *International Journal of Physical Distribution and Logistics Management*, *38*(5), 360–387. https://doi.org/10.1108/09600030810882816

Chauhan, C., Singh, A., & Luthra, S. (2021). Barriers to industry 4.0 adoption and its performance implications: An empirical investigation of emerging economy. *Journal of Cleaner Production*, *285*, 124809. https://doi.org/10.1016/j.jclepro.2020.124809

Che, L., Zhang, Y., Wang, J., & Bai, M. (2020). A new method for deriving weights in group fuzzy analytic hierarchy process and evaluation measures. *IFAC PapersOnLine*, *53*(2), 7941–7946. https://doi.org/10.1016/j.ifacol.2020.12.2183

Chhabra, D., & Singh, R. K. (2022). Analyzing barriers to green logistics in context of circular economy and Industry 4.0 in the Indian manufacturing industry. *International Journal of Logistics Research and Applications*. https://doi.org/10.1080/13675567.2022.2134847

Coffey, L., & Claudio, D. (2021). In defense of group fuzzy AHP: A comparison of group fuzzy AHP and group AHP with confidence intervals. *Expert Systems with Applications*, *178*, 114970. https://doi.org/10.1016/j.eswa.2021.114970

Cotter, M., & Asch, F. (2020). Editorial: Smallholder targeted agriculture 4.0 in temperature limited cropping system. *Journal of Agronomy and Crop Science*, *206*(4), 421–422. https://doi.org/10.1111/jac.12414

Creswell, J. W. (1999). Mixed-method research: introduction and application. In *Handbook of educational policy—Educational psychology* (pp. 455–472). Academic Press Inc. https://doi.org/10.1016/B978-012174698-8/50045-X

Cricelli, L., Mauriello, R., Strazzullo, S., & Camilleri, M. A. (2024). Assessing the impact of Industry 4.0 technologies on the social sustainability of agrifood companies. *Business Strategy and the Environment*. https://doi.org/10.1002/bse.3874

Cui, Y., Liu, W., Rani, P., & Alrasheedi, M. (2021). Internet of things (IoT) adoption barriers for the circular economy using Pythagorean fuzzy SWARA-CoCoSo decision-making approach in the manufacturing sector. *Technological Forecasting and Social Change*, *171*, 120951. https://doi.org/10.1016/j.techfore.2021.120951

Dalenogare, L. S., Benitez, G. B., Ayala, N. F., & Frank, A. G. (2018). The expected contribution of I4.0 technologies for industrial performance. *International Journal of Production Economics*, *204*, 383–394. https://doi.org/10.1016/j.ijpe.2018.08.019

Deloitte. 2020. Industry 4.0: At the intersection of readiness and responsibility. Available at: https://www2.deloitte.com/us/en/insights/deloitte-review/issue-22/industry-4-0-technology-manufacturing-revolution.html [Accessed: 18/09/2023].

Doyle, L., Brady, A.-M., & Byrne, G. (2009). An overview of mixed methods research. *Journal of Research in Nursing*, *14*(2), 175–185.

Dwivedi, A., Moktadir, M. A., Jabbour, C. J. C., & De Carvalho, D. E. (2022). Integrating the circular economy and I4.0 for sustainable development: Implications for responsible footwear production in a big data-driven world. *Technological Forecasting and Social Change*, *175*, 121335. https://doi.org/10.1016/j.techfore.2021.121335

Dwivedi, A., & Paul, S. K. (2022). A framework for digital supply chains in the era of circular economy: Implications on environmental sustainability. *Business Strategy and the Environment*, *31*, 1249–1274. https://doi.org/10.1002/bse.2953

Dyer, R. F., & Forman, E. H. (1992). Group decision support with the analytic hierarchy process. *Decision Support Systems*, *8*, 99–124. https://doi.org/10.1016/0167-9236(92)90003-8

Elkington, J. (1997). Cannibals with forks. In *The triple bottom line of 21st century* (pp. 1–16). Capstone Publishing Limited.

European Environmental Agency. 2021. Unlocking the potential of Industry 4.0 to reduce the environmental impact of production. Available at: https://www.eionet.europa.eu/etcs/etc-wmge/products/etc-wmge-reports/unlocking-the-potential-of-industry-4-0-to-reduce-the-environmental-impact-of-production [Accessed: 14/05/2024].

FAO. 2014. Developing sustainable food value chains—Guiding principles. Available at: https://www.fao.org/3/i3953e/i3953e.pdf [Accessed: 07/06/2023].

FAO. 2022. Greenhouse gap emissions from agrifood systems. Available at: https://www.fao.org/3/cc2672en/cc2672en.pdf [Accessed: 18/09/2023].

FAO. 2023. Achieving SDG2 without breaching the 1.5C threshold: A global roadmap. Available at: https://www.fao.org/interactive/sdg2-roadmap/assets/3d-models/inbrief-roadmap.pdf [Accessed: 16/05/2024].

Feng, H., Wang, X., Duan, Y., Zhang, J., & Zhang, X. (2020). Applying blockchain technology to improve agri-food traceability: A review of development methods, benefits and challenges. *Journal of Cleaner Production*, *260*, 121031. https://doi.org/10.1016/j.jclepro.2020.121031

Gebhardt, M., Kopyto, M., Birkel, H., & Hartmann, E. (2022). I4.0 technologies as enablers of collaboration in circular supply chains: A systematic literature review. *International Journal of Production Research*, *60*(23), 6967–6995. https://doi.org/10.1080/00207543.2021.1999521

Ghobakhloo, M., Fathi, M., Iranmanesh, M., Maroufkhani, P., & Morales, M. E. (2021). I4.0 ten years on: A bibliometric and systematic review of concepts, sustainability value drivers, and success determinants. *Journal of Cleaner Production*, *302*, 127052. https://doi.org/10.1016/j.jclepro.2021.127052

Ghobakhloo, M., Iranmanesh, M., Grybauskas, A., Vilkas, M., & Petraite, M. (2021). Industry 4.0, innovation, and sustainable development: A systematic review and a roadmap to sustainable innovation. *Business Strategy and the Environment*, *30*(8), 4237–4257.

Gligor, D., Bozkurt, S., Russo, I., & Omar, A. (2019). A look into the past and future: Theories within supply chain management, marketing and management. *Supply Chain Management: an International Journal*, *24*(1), 170–186. https://doi.org/10.1108/SCM-03-2018-0124

Govindan, K. (2022). Tunneling the barriers of blockchain technology in remanufacturing for achieving sustainable development goals: A circular manufacturing perspective. *Business Strategy and the Environment*, *31*, 3769–3785. https://doi.org/10.1002/bse.3031

Govindan, K., Kaliyan, M., Kannan, D., & Haq, A. N. (2014). Barrier analysis for green supply chain management implementation in Indian industries using analytic hierarchy process. *International Journal of Production Economics*, *147*, 555–568. https://doi.org/10.1016/j.ijpe.2013.08.018

Guo, J., Yu, Z., Ma, Z., Xu, D., & Cao, S. (2022). What factors have driven urbanization in China? *Environment, Development and Sustainability*, *24*, 6508–6526. https://doi.org/10.1007/s10668-021-01714-4

Halcomb, E. J. (2019). Mixed methods research: The issues beyond combining methods. *Journal of Advanced Nursing*, *75*(3), 499–501. https://doi.org/10.1111/jan.13877

Hasna, A. M. (2010). Sustainability classifications in engineering: Discipline and approach. *International Journal of Sustainable Engineering*, *3*(4), 258–276. https://doi.org/10.1080/19397038.2010.500743

Joshi, S., Singh, R. K., & Sharma, M. (2023). Sustainable agri-food supply chain practices: Few empirical evidences from a developing economy. *Global Business Review*, *24*(3), 451–474. https://doi.org/10.1177/0972150920907014

Jurevičienė, D., & Skvarciany, V. (2016). Camels +T approach for banks' soundness assessment: Evidence from the Baltics. *Entrepreneurship and Sustainability Issues*, *4*(2), 159–173. https://doi.org/10.9770/jesi.2016.4.2(4)

Kamble, S. S., Gunasekaran, A., & Sharma, R. (2018). Analysis of the driving and dependence power of barriers to adopt industry 4.0 in Indian manufacturing industry. *Computers in Industry*, *101*, 107–119. https://doi.org/10.1016/j.compind.2018.06.004

Karadayi-Usta, S. (2020). An interpretive structural analysis for Industry 4.0 adoption challenges. *IEEE Transactions on Engineering Management*, *67*(3), 973–978. https://doi.org/10.1109/TEM.2018.2890443

Khan, S., Haleem, A., Husain, Z., Samson, D., & Pathak, R. D. (2023). Barriers to blockchain technology adoption in supply chains: The case of India. *Operations Management Research*, *16*, 668–683. https://doi.org/10.1007/s12063-023-00358-z

Kim, W.-S., Lee, W.-S., & Kim, Y.-J. (2020). A review of the applications of the internet of things (IoT) for agricultural automation. *Journal of Biosystems Engineering*, *45*, 385–400. https://doi.org/10.1007/s42853-020-00078-3

Kouhizadeh, M., Saberi, S., & Sarkis, J. (2021). Blockchain technology and the sustainable supply chain: Theoretically exploring adoption barriers. *International Journal of Production Economics*, *231*, 107831. https://doi.org/10.1016/j.ijpe.2020.107831

Kumar, P., Brar, P. S., Singh, D., & Bhamu, J. (2022). Fuzzy AHP approach for barriers to implement LSS in the context of I4.0. *International Journal of Productivity and Performance Management*, *72*, 2559–2583. https://doi.org/10.1108/IJPPM-12-2021-0715

Kumar, S., Raut, R. D., Nayal, K., Kraus, S., Yadav, V. S., & Narkhede, B. E. (2021). To identify I4.0 and circular economy adoption barriers in the agriculture supply chain by using ISM-ANP. *Journal of Cleaner Production*, *293*, 126023. https://doi.org/10.1016/j.jclepro.2021.126023

Kumar, P., Singh, R. K., & Kumar, V. (2021). Managing supply chains for sustainable operations in the era of industry 4.0 and circular economy: Analysis of barriers. *Resources, Conservation and Recycling*, *164*, 105215. https://doi.org/10.1016/j.resconrec.2020.105215

Li, K., Lee, J.-Y., & Gharehgozli, A. (2023). Blockchain in food supply chains: A literature review and synthesis analysis of platforms, benefits and challenges. *International Journal of Production Research*, *61*(11), 3527–3546. https://doi.org/10.1080/00207543.2021.1970849

Li, X., & Liao, H. (2023). A large-scale group decision making method based on spatial information aggregation and empathetic relationships of experts. *Information Sciences*, *632*, 503–515. https://doi.org/10.1016/j.ins.2023.03.051

Liu, C., Wang, X., Bai, Z., Wang, H., & Li, C. (2023). Does digital technology application promote carbon emission efficiency in dairy farms? Evidence from China. *Agriculture*, *13*(4), 904.

Lu, H., Zhao, G., & Liu, S. (2024). Integrating circular economy and I4.0 for sustainable supply chain management: A dynamic capability view. *Production Planning & Control*, *35*(2), 170–186. https://doi.org/10.1080/09537287.2022.2063198

Luthra, S., & Mangla, S. K. (2018). Evaluating challenges to Industry 4.0 initiatives for supply chain sustainability in emerging economies. *Process Safety and Environmental Protection*, *117*, 168–179. https://doi.org/10.1016/j.psep.2018.04.018

Mahajan, H. B., Junnarkar, A. A., Tiwari, M., Tiwari, T., & Upadhyaya, M. (2022). LCIPA: Lightweight clustering protocol for I4.0 enabled precision agriculture. *Microprocessors and Microsystems*, *94*, 104633. https://doi.org/10.1016/j.micpro.2022.104633

Majumdar, A., Garg, H., & Jain, R. (2021). Managing the barriers of I4.0 adoption and implementation in textile and clothing industry: Interpretive structural model and triple helix framework. *Computers in Industry*, *125*, 103372. https://doi.org/10.1016/j.compind.2020.103372

Majumdar, A., Sinha, S. K., & Govindan, K. (2021). Prioritising risk mitigation strategies for environmental sustainable clothing supply chains: Insights from selected organisational theories. *Sustainable Production and Consumption*, *28*, 543–555.

Mangla, S. K., Kazancoglu, Y., Yildizbasi, A., Ozturk, C., & Calik, A. (2022). A conceptual framework for blockchain-based sustainable supply chain and evaluating implementation barriers: A case of the tea supply chain. *Business Strategy and the Environment*, *31*, 3693–3716. https://doi.org/10.1002/bse.3027

Mantravadi, S., Srai, J. S., & Moller, C. (2023). Application of MES/MOM for I4.0 supply chains: A cross-case analysis. *Computers in Industry*, *148*, 103907. https://doi.org/10.1016/j.compind.2023.103907

Markman, G. D., & Krause, D. (2016). Theory building surrounding sustainable supply chain management: Assessing what we know, exploring where to go. *Journal of Supply Chain Management*, *52*(2), 3–10. https://doi.org/10.1111/jscm.12105

Martins, C. L., & Pato, M. V. (2019). Supply chain sustainability: A tertiary literature review. *Journal of Cleaner Production*, *225*, 995–1016. https://doi.org/10.1016/j.jclepro.2019.03.250

Masood, T., & Sonntag, P. (2020). Industry 4.0: Adoption challenges and benefits for SMEs. *Computers in Industry*, *121*, 103261. https://doi.org/10.1016/j.compind.2020.103261

Mathivathanan, D., Mathiyazhagan, K., Rana, N. P., Khorana, S., & Dwivedi, Y. K. (2021). Barriers to the adoption of blockchain technology in business supply chains: A total interpretive structural modelling (TISM) approach. *International Journal of Production Research*, *59*(11), 3338–3359. https://doi.org/10.1080/00207543.2020.1868597

Mathiyazhagan, K., Govindan, K., NoorulHaq, A., & Geng, Y. (2013). An ISM approach for the barrier analysis in implementing green supply chain management. *Journal of Cleaner Production*, *47*, 283–297. https://doi.org/10.1016/j.jclepro.2012.10.042

McAdam, R., Miller, K., & McSorley, C. (2019). Towards a contingency theory perspective of quality management in enabling strategic alignment. *International Journal of Production Economics*, *207*, 195–209. https://doi.org/10.1016/j.ijpe.2016.07.003

McKinsey & Company. (2023). Agtech: Breaking down the farmer adoption dilemma. Available at: https://www.mckinsey.com/industries/agriculture/our-insights/agtech-breaking-down-the-farmer-adoption-dilemma [Accessed: 13/02/2024].

Misra, N. N., Al-Mallahi, A., Bhullar, M. S., Upadhyay, R., & Martynenko, A. (2022). IoT, big data, and artificial intelligence in agriculture and food industry. *IEEE Internet of Things Journal*, *9*(9), 6305–6324. https://doi.org/10.1109/JIOT.2020.2998584

Molex. (2021). The state of Industry 4.0: A survey of industrial manufacturing stakeholders. Available at: https://experience.molex.com/webfoo/wp-content/uploads/2021/07/Survey-Report-Industry-4.pdf [Accessed: 18/09/2023].

National Assembly for Wales. (2018). Industry 4.0—The future of Wales. Available at: https://senedd.wales/laid%20documents/cr-ld11717/cr-ld11717-e.pdf [Accessed: 13/02/2024].

National Bureau of Statistics of China. (2022). China statistical yearbook 2022. Available at: http://www.stats.gov.cn/sj/ndsj/2022/indexch.htm [Accessed: 08/09/2023].

Nawandar, N. K., & Satpute, V. R. (2019). IoT based low cost and intelligent module for smart irrigation system. *Computers and Electronics in Agriculture*, *162*, 979–990. https://doi.org/10.1016/j.compag.2019.05.027

Nimawat, D., & Gidwani, B. D. (2021). Prioritization of barriers for Industry 4.0 adoption in the context of Indian manufacturing industries using AHP and ANP analysis. *International Journal of Computer Integrated Manufacturing*, *34*(11), 1139–1161. https://doi.org/10.1080/0951192X.2021.1963481

Ozkan-Ozen, Y. D., Kazancoglu, Y., & Mangla, S. K. (2020). Synchronized barriers for circular supply chains in Industry 3.5/I4.0 transition for sustainable resource management. *Resources, Conservation and Recycling*, *161*, 104986. https://doi.org/10.1016/j.resconrec.2020.104986

Parente, M., Figueira, G., Amorim, P., & Marques, A. (2020). Production scheduling in the context of I4.0: Review and trends. *International Journal of Production Research*, *58*(17), 5401–5431. https://doi.org/10.1080/00207543.2020.1718794

Piccarozzi, M., Silvestri, C., Aquilani, B., & Silvestri, L. (2022). Is this a new story of the two giants? A systematic literature review of the relationship between I4.0, sustainability and its pillars. *Technological Forecasting and Social Change*, *177*, 121511. https://doi.org/10.1016/j.techfore.2022.121511

Prajapati, D. K., Mathiyazhagan, K., Agarwal, V., Vijaya Sunder, M., Khorana, S., & Gunasekaran, A. (2024). Enabling industry 4.0: Assessing technologies and prioritization framework for agile manufacturing in India. *Journal of Cleaner Production*, *447*, 141488. https://doi.org/10.1016/j.jclepro.2024.141488

Qin, J., Liu, Y., & Grosvenor, R. (2016). A categorical framework of manufacturing for I4.0 and beyond. *Procedia CIRP*, *52*, 173–178. https://doi.org/10.1016/j.procir.2016.08.005

Queiroz, M. M., Pereira, S. C. F., Telles, R., & Machado, M. C. (2021). I4.0 and digital supply chain capabilities: A framework for understanding digitalization challenges and opportunities. *Benchmarking: an International Journal*, *28*(5), 1761–1782. https://doi.org/10.1108/BIJ-12-2018-0435

Raj, A., Dwivedi, G., Sharma, A., De Sousa Jabbour, A. B. L., & Rajak, S. (2020). Barriers to the adoption of industry 4.0 technologies in the manufacturing sector: An inter-country comparative perspective. *International Journal of Production Economics*, *224*, 107546. https://doi.org/10.1016/j.ijpe.2019.107546

Deepu, T. S., & Ravi, V. (2023). An ISM-MICMAC approach for analyzing dependencies among barriers of supply chain digitalization. *Journal of Modelling in Management*, *18*(3), 817–841.

Ren, Y., Wu, K.-J., Lim, M. K., & Tseng, M.-L. (2023). Technology transfer adoption to achieve a circular economy model under resource-based view: A high-tech firm. *International Journal of Production Economics*, *264*, 108983. https://doi.org/10.1016/j.ijpe.2023.108983

Saaty, T. L. (1996). *Decision making with dependence and feedback: The analytic network process*. RWS Publications.

Saaty, T. L., & Tran, L. T. (2010). Fuzzy judgements and fuzzy sets. *International Journal of Strategic Decision Science*, *1*(1), 23–40. https://doi.org/10.4018/jsds.2010103002

Sanchez, R., & Heene, A. (2017). Building theory for management science and practice: an epistemological perspective from competence-based management theory. In R. Sanchez, A. Heene, S. Polat, & U. Asan (Eds.), *Mid-range management theory: Competence perspectives on modularity and dynamic capabilities* (Vol. 8, pp. 1–23).

Sarkar, B. D., & Shankar, R. (2021). Understanding the barriers of port logistics for effective operation in the Industry 4.0 era: Data-driven decision making. *International Journal of Information Management Data Insights*, *1*, 100031. https://doi.org/10.1016/j.jjimei.2021.100031

Saunders, M., Lewis, P., & Thornhill, A. (2009). *Research methods for business students* (5th ed.). Pearson Education Limited.

Schwartz, S. H. (2006). A theory of cultural value orientations: Explication and applications. *Comparative Sociology*, *5*(2–3), 137–182. https://doi.org/10.1163/156913306778667357

Senna, P. P., Ferreira, L. M. D. F., Barros, A. C., Roca, J. B., & Magalhaes, V. (2022). Prioritizing barriers for the adoption of I4.0 technologies. *Computers & Industrial Engineering*, *171*, 108428. https://doi.org/10.1016/j.cie.2022.108428

Shang, C., Saeidi, P., & Goh, C. F. (2022). Evaluation of circular supply chains barriers in the era of Industry 4.0 transition using an extended decision-making approach. *Journal of Enterprise Information Management*, *35*(4/5), 1100–1128. https://doi.org/10.1108/JEIM-09-2021-0396

Shuvabrata, C., Ankit, S., & Omkarprasad S, V. (2020). Achieving sustainable operational excellence through IT implementation in Indian logistics sector: An analysis of barriers. *Resources, Conservation and Recycling*, *152*, 104506. https://doi.org/10.1016/j.resconrec.2019.104506

Si, S.-L., You, X.-Y., Liu, H.-C., & Zhang, P. (2018). DEMATEL technique: A systematic review of the state-of-the-art literature on methodologies and applications. *Mathematical Problems in Engineering*, *2018*, 1–33. https://doi.org/10.1155/2018/3696457

Sicular, T., Yang, X., & Gustafsson, B. (2022). The rise of China's global middle class in an international context. *China & World Economy*, *30*(1), 5–27. https://doi.org/10.1111/cwe.12400

Singh, R. K., Mathiyazhagan, K., Scuotto, V., & Pironti, M. (2024). Green open innovation and circular economy: Investigating the role of big data management and sustainable supply chain. *IEEE Transactions on Engineering Management*, *71*, 8417–8429. https://doi.org/10.1109/TEM.2024.3387107

Srhir, S., Jaegler, A., & Montaya-Torres, J. R. (2023). Uncovering Industry 4.0 technology attributes in sustainable supply chain 4.0: A systematic literature review. *Business Strategy and the Environment*, *32*, 4143–4166. https://doi.org/10.1002/bse.3358

State Council. (2020). China takes training of high-quality farmers to new level. Available at: https://english.www.gov.cn/statecouncil/ministries/202011/26/content_WS5fbf0869c6d0f72576940b21.html [Accessed: 14/02/2024].

State Council. (2021). Notice of agricultural and rural modernization planning. Available at: http://www.gov.cn/zhengce/content/2022-02/11/content_5673082.htm [Accessed: 24/05/2023].

Stefanini, R., & Vignali, G. (2022). The environmental, economic and social impact of I4.0 in the food sector: A descriptive literature review. *IFAC-PapersOnline*, *55*(10), 1497–1502. https://doi.org/10.1016/j.ifacol.2022.09.602

Stentoft, J., Wickstrom, K. A., Philipsen, K., & Haug, A. (2021). Drivers and barriers for I4.0 readiness and practice: Empirical evidence from small and medium-sized manufacturers. *Production Planning & Control*, *32*(10), 811–828. https://doi.org/10.1080/09537287.2020.1768318

Sushil. (2012). Interpreting the interpretive structural model. *Global Journal of Flexible Systems Management*, *13*(2), 87–106. https://doi.org/10.1007/s40171-012-0008-3

Taddei, E., Sassanelli, C., Rosa, P., & Terzi, S. (2022). Circular supply chains in the era of I4.0: A systematic literature review. *Computers & Industrial Engineering*, *170*, 108268. https://doi.org/10.1016/j.cie.2022.108268

Taddei, E., Sassanelli, C., Rosa, P., & Terzi, S. (2024). Circular supply chains theoretical gaps and practical barriers: A model to support approaching firms in the era of industry 4.0. *Computers & Industrial Engineering*, *190*, 110049. https://doi.org/10.1016/j.cie.2024.110049

Tang, M., & Liao, H. (2021). From conventional group decision making to large-scale group decision making: What are the challenges and how to meet them in big data era? A state-of-the-art survey. *Omega*, *100*, 102141. https://doi.org/10.1016/j.omega.2019.102141

Timans, R., Wouters, P., & Heilbron, J. (2019). Mixed methods research: What it is and what it could be. *Theory and Society*, *48*, 193–216. https://doi.org/10.1007/s11186-019-09345-5

Touboulic, A., & Walker, H. (2015). Theories in sustainable supply chain management: A structured literature review. *International Journal of Physical Distribution and Logistics Management*, *45*(1/2), 16–42. https://doi.org/10.1108/IJPDLM-05-2013-0106

Trevisan, A. H., Lobo, A., Guzzo, D., De Vasconcelos Gomes, L. A., & Mascarenhas, J. (2023). Barriers to employing digital technologies for a circular economy: A multi-level perspective. *Journal of Environmental Management*, *332*, 117437. https://doi.org/10.1016/j.jenvman.2023.117437

Turner, J. H., & Boyns, D. E. (2002). The return of grand theory. In J. H. Turner (Ed.), *Handbook of sociological theory. Handbooks of sociology and social research*. Springer. https://doi.org/10.1007/0-387-36274-6

Ul-Durar, S., Awan, U., Varma, A., Memon, S., & Mention, A.-L. (2023). Integrating knowledge management and orientation dynamics for organization transition from eco-innovation to circular economy. *Journal of Knowledge Management*, *27*(8), 2217–2248. https://doi.org/10.1108/JKM-05-2022-0424

USDA. (2023). Sustainable agriculture. Available at: https://www.nal.usda.gov/farms-and-agricultural-production-systems/sustainable-agriculture#:~:text=Sustainable%20agriculture%20is%20farming%20in,best%20use%20of%20nonrenewable%20resources [Accessed: 06/06/2023].

Wang, Y.-M., & Elhag, T. M. S. (2007). A fuzzy group decision making approach for bridge risk assessment. *Computers & Industrial Engineering*, *53*, 137–148. https://doi.org/10.1016/j.cie.2007.04.009

Widodo. (2018). Grand theory model of strategy quality: Strategic asset approach at industry. *Academy of Strategic Management Journal*, *17*(2), 1–10.

World Commission on Environment and Development. (1987). *Our common future*. Oxford University Press.

Xu, L. D., Xu, E. L., & Li, L. (2018). I4.0: State of the art and future trends. *International Journal of Production Research*, *56*(8), 2941–2962. https://doi.org/10.1080/00207543.2018.1444806

Yang, Q., Du, X., Wang, Z., Meng, Z., Ma, Z., & Zhang, Q. (2023). A review of core agricultural robot technologies for crop productions. *Computers and Electronics in Agriculture*, *206*, 107701. https://doi.org/10.1016/j.compag.2023.107701

Yilmaz, A., Dora, M., Hezarkhani, B., & Kumar, M. (2022). Lean and I4.0: Mapping determinants and barriers from a social, environmental, and operational perspective. *Technological Forecasting and Social Change*, *175*, 121320. https://doi.org/10.1016/j.techfore.2021.121320

Zhao, G., Chen, H., Liu, S., Dennehy, D., Jones, P., & Lopez, C. (2023). Analysis of factors affecting cross-boundary knowledge mobilization in agri-food supply chains: An integrated approach. *Journal of Business Research*, *164*, 114006. https://doi.org/10.1016/j.jbusres.2023.114006

Zhao, G., Liu, S., Lopez, C., Chen, H., Lu, H., Mangla, S. K., & Elgueta, S. (2020). Risk analysis of the Agri-food supply chain: A multi-method approach. *International Journal of Production Research*, *58*(16), 4851–4876. https://doi.org/10.1080/00207543.2020.1725684

Zhao, G., Liu, S., Lopez, C., Lu, H., Elgueta, S., Chen, H., & Boshkoska, B. M. (2019). Blockchain technology in agri-food value chain management: A synthesis of applications, challenges and future research directions. *Computers in Industry*, *109*, 83–99. https://doi.org/10.1016/j.compind.2019.04.002

Zhao, G., Xie, X., Wang, Y., Liu, S., Jones, P., & Lopez, C. (2024). Barrier analysis to improve big data analytics capability of the maritime industry: A mixed-method approach. *Technological Forecasting and Social Change*, *203*, 123345. https://doi.org/10.1016/j.techfore.2024.123345

Zhao, G., Zhao, G., Zubairu, N., Chen, X., Olan, F., Dennehy, D., & Jones, P. (2024). Understanding supply chain resilience as a multi-level framework: a systematic literature review. In *Lecture notes in business information processing* (Vol. 506). Springer.

Zheng, T., Ardolino, M., Bacchetti, A., & Perona, M. (2021). The applications of I4.0 technologies in manufacturing context: A systematic literature review. *International Journal of Production Research*, *59*(6), 1922–1954. https://doi.org/10.1080/00207543.2020.1824085

Zhu, B., & Xu, Z. (2014). Analytic hierarchy process—Hesitant group decision making. *European Journal of Operational Research*, *239*, 794–801. https://doi.org/10.1016/j.ejor.2014.06.019

Zhu, W., Jia, S., Devineni, N., Lv, A., & Lall, U. (2019). Evaluating China's water security for food production: The role of rainfall and irrigation. *Geophysical Research Letters*, *46*(20), 11155–11166. https://doi.org/10.1029/2019GL083226

How to cite this article: Zhao, G., Ye, C., Dennehy, D., Liu, S., Harfouche, A., & Olan, F. (2024). Analysis of barriers to adopting Industry 4.0 to achieve agri-food supply chain sustainability: A group-based fuzzy analytic hierarchy process. *Business Strategy and the Environment*, 1–28. https://doi.org/10.1002/bse.3928

APPENDIX A: INTERVIEW GUIDE FOR EVALUATING BARRIERS

1. How do you view the following barriers to I4.0 adoption to achieve AFSC sustainability? Please tick (√) in the following table.

I4.0 adoption barriers to achieve AFSC sustainability			Descriptor				
			Strongly agree	Agree	Neutral	Disagree	Strongly disagree
	Technological barriers						
		…					
	Any other barriers?						
	Economic barriers						
		…					
	Any other barriers?						
	Social barriers						
		…					
	Any other barriers?						
	Environmental barriers						
		…					
	Any other barriers?						
	Organizational barriers						
		…					
	Any other barriers?						
	Supply chain barriers						
		…					
	Any other barriers?						

2. If you disagree or strongly disagree with these barriers to I4.0 adoption to achieve AFSC sustainability, please tell me why.

APPENDIX B: GFAHP CALCULATION PROCESS

B.1 Experts' pairwise matrices for dimensions

Expert 1's pairwise matrix M^1						
DM1(M^1)	**T**	**E**	**S**	**N**	**O**	**C**
T	(1,1,1)	(2,3,4)	(1/5,1/4,1/3)	(1/7,1/6,1/5)	(1,2,3)	(1/4,1/3,1/2)
E	(1/4,1/3,1/2)	(1,1,1)	(1/9,1/8,1/7)	(1/9,1/9,1/8)	(1/3,1/2,1/1)	(1/8,1/7,1/6)
S	(3,4,5)	(7,8,9)	(1,1,1)	(1/3,1/2,1/1)	(6,7,8)	(3,4,5)
N	(5,6,7)	(8,9,9)	(1,2,3)	(1,1,1)	(7,8,9)	(3,4,5)
O	(1/3,1/2,1/1)	(1,2,3)	(1/8,1/7,1/6)	(1/9,1/8,1/7)	(1,1,1)	(1/6,1/5,1/4)
C	(2,3,4)	(6,7,8)	(1/5,1/4,1/3)	(1/5,1/4,1/3)	(4,5,6)	(1,1,1)
Expert 2's pairwise matrix M^2						
DM2(M^2)	**T**	**E**	**S**	**N**	**O**	**C**
T	(1,1,1)	(1,2,3)	(1/6,1/5,1/4)	(1/9,1/8,1/7)	(1/4,1/3,1/2)	(1/8,1/7,1/6)
E	(1/3,1/2,1/1)	(1,1,1)	(1/8,1/7,1/6)	(1/9,1/9,1/8)	(1/5,1/4,1/3)	(1/9,1/8,1/7)
S	(4,5,6)	(6,7,8)	(1,1,1)	(1/4,1/3,1/2)	(1,2,3)	(1/3,1/2,1/1)
N	(7,8,9)	(8,9,9)	(2,3,4)	(1,1,1)	(5,6,7)	(1,2,3)
O	(2,3,4)	(3,4,5)	(1/3,1/2,1/1)	(1/7,1/6,1/5)	(1,1,1)	(1/6,1/5,1/4)
C	(6,7,8)	(7,8,9)	(1,2,3)	(1/3,1/2,1/1)	(4,5,6)	(1,1,1)
Expert 3's pairwise matrix M^3						
DM3(M^3)	**T**	**E**	**S**	**N**	**O**	**C**
T	(1,1,1)	(4,5,6)	(1/4,1/3,1/2)	(1/9,1/8,1/7)	(6,7,8)	(1/6,1/5,1/4)
E	(1/6,1/5,1/4)	(1,1,1)	(1/5,1/4,1/3)	(1/9,1/9,1/8)	(1,2,3)	(1/8,1/7,1/6)
S	(2,3,4)	(3,4,5)	(1,1,1)	(1/5,1/4,1/3)	(5,6,7)	(1/3,1/2,1/1)
N	(7,8,9)	(8,9,9)	(3,4,5)	(1,1,1)	(8,9,9)	(1,2,3)
O	(1/8,1/7,1/6)	(1/3,1/2,1/1)	(1/7,1/6,1/5)	(1/9,1/9,1/8)	(1,1,1)	(1/8,1/7,1/6)
C	(4,5,6)	(6,7,8)	(1,2,3)	(1/3,1/2,1/1)	(6,7,8)	(1,1,1)

B.2 Random index based on the order of matrix

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

B.3 The weighting of dimension of each expert

Dimension	DM1	DM2	DM3
T	0.070778	0.039933	0.085728
E	0.028162	0.027392	0.035954
S	0.296240	0.164575	0.151826
N	0.416415	0.405021	0.437943
O	0.041870	0.083569	0.025218
C	0.146535	0.279511	0.263331
CR (C_D^n)	0.043268	0.029973	0.076203

B.4 Experts' pairwise matrices for barriers

The experts' pairwise matrices for technological barriers

Expert 1's pairwise matrix MT^1							
DM1	**T1**	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**
T1	(1,1,1)	(1/9,1/8,1/7)	(1/8,1/7,1/6)	(1/7,1/6,1/5)	(1,2,3)	(1/6,1/5,1/4)	(1/3,1/2,1/1)
T2	(7,8,9)	(1,1,1)	(1,2,3)	(2,3,4)	(8,9,9)	(3,4,5)	(4,5,6)
T3	(6,7,8)	(1/3,1/2,1/1)	(1,1,1)	(1,2,3)	(6,7,8)	(3,4,5)	(6,7,8)
T4	(5,6,7)	(1/4,1/3,1/2)	(1/3,1/2,1/1)	(1,1,1)	(5,6,7)	(1,2,3)	(3,4,5)
T5	(1/3,1/2,1/1)	(1/9,1/9,1/8)	(1/8,1/7,1/6)	(1/7,1/6,1/5)	(1,1,1)	(1/7,1/6,1/5)	(1/5,1/4,1/3)
T6	(4,5,6)	(1/5,1/4,1/3)	(1/5,1/4,1/3)	(1/3,1/2,1/1)	(5,6,7)	(1,1,1)	(1,2,3)
T7	(1,2,3)	(1/6,1/5,1/4)	(1/8,1/7,1/6)	(1/5,1/4,1/3)	(3,4,5)	(1/3,1/2,1/1)	(1,1,1)
Expert 2's pairwise matrix MT^2							
DM2	**T1**	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**
T1	(1,1,1)	(1/9,1/9,1/8)	(1/7,1/6,1/5)	(1/9,1/8,1/7)	(3,4,5)	(1/3,1/2,1/1)	(2,3,4)
T2	(8,9,9)	(1,1,1)	(2,3,4)	(1,2,3)	(7,8,9)	(3,4,5)	(5,6,7)
T3	(5,6,7)	(1/4,1/3,1/2)	(1,1,1)	(1/3,1/2,1/1)	(6,7,8)	(1,2,3)	(5,6,7)
T4	(7,8,9)	(1/3,1/2,1/1)	(1,2,3)	(1,1,1)	(7,8,9)	(4,5,6)	(6,7,8)
T5	(1/5,1/4,1/3)	(1/9,1/8,1/7)	(1/8,1/7,1/6)	(1/9,1/8,1/7)	(1,1,1)	(1/7,1/6,1/5)	(1/3,1/2,1/1)
T6	(1,2,3)	(1/5,1/4,1/3)	(1/3,1/2,1/1)	(1/6,1/5,1/4)	(5,6,7)	(1,1,1)	(3,4,5)
T7	(1/4,1/3,1/2)	(1/7,1/6,1/5)	(1/7,1/6,1/5)	(1/8,1/7,1/6)	(1,2,3)	(1/5,1/4,1/3)	(1,1,1)
Expert 3's pairwise matrix MT^3							
DM3	**T1**	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**
T1	(1,1,1)	(1/9,1/8,1/7)	(1/9,1/9,1/8)	(1/8,1/7,1/6)	(1/4,1/3,1/2)	(1/6,1/5,1/4)	(1/5,1/4,1/3)
T2	(7,8,9)	(1,1,1)	(1/3,1/2,1/1)	(1,2,3)	(6,7,8)	(4,5,6)	(5,6,7)
T3	(8,9,9)	(1,2,3)	(1,1,1)	(3,4,5)	(7,8,9)	(4,5,6)	(5,6,7)
T4	(6,7,8)	(1/3,1/2,1/1)	(1/5,1/4,1/3)	(1,1,1)	(5,6,7)	(1,2,3)	(2,3,4)
T5	(2,3,4)	(1/8,1/7,1/6)	(1/9,1/8,1/7)	(1/7,1/6,1/5)	(1,1,1)	(1/6,1/5,1/4)	(1/3,1/2,1/1)
T6	(4,5,6)	(1/6,1/5,1/4)	(1/6,1/5,1/4)	(1/3,1/2,1/1)	(4,5,6)	(1,1,1)	(1,2,3)
T7	(3,4,5)	(1/7,1/6,1/5)	(1/7,1/6,1/5)	(1/4,1/3,1/2)	(1,2,3)	(1/3,1/2,1/1)	(1,1,1)

The experts' pairwise matrices for economic barriers

Expert 1's pairwise matrix ME^1			
DM1	**E1**	**E2**	**E3**
E1	(1,1,1)	(1/3,1/2,1/1)	(1/7,1/6,1/5)
E2	(1,2,3)	(1,1,1)	(1/6,1/5,1/4)
E3	(5,6,7)	(4,5,6)	(1,1,1)
Expert 2's pairwise matrix ME^2			
DM2	**E1**	**E2**	**E3**
E1	(1,1,1)	(1,2,3)	(1/4,1/3,1/2)
E2	(1/3,1/2,1/1)	(1,1,1)	(1/5,1/4,1/3)
E3	(2,3,4)	(3,4,5)	(1,1,1)
Expert 3's pairwise matrix ME^3			
DM3	**E1**	**E2**	**E3**
E1	(1,1,1)	(1/5,1/4,1/3)	(1/4,1/3,1/2)
E2	(3,4,5)	(1,1,1)	(1,2,3)
E3	(2,3,4)	(1/3,1/2,1/1)	(1,1,1)

The experts' pairwise matrices for social barriers

Expert 1's pairwise matrix MS^1						
DM1	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**
S1	(1,1,1)	(1/4,1/3,1/2)	(1,2,3)	(1/6,1/5,1/4)	(1/5,1/4,1/3)	(3,4,5)
S2	(2,3,4)	(1,1,1)	(2,3,4)	(1/5,1/4,1/3)	(1/3,1/2,1/1)	(5,6,7)
S3	(1/3,1/2,1/1)	(1/4,1/3,1/2)	(1,1,1)	(1/8,1/7,1/6)	(1/7,1/6,1/5)	(2,3,4)
S4	(4,5,6)	(3,4,5)	(6,7,8)	(1,1,1)	(1,2,3)	(7,8,9)
S5	(3,4,5)	(1,2,3)	(5,6,7)	(1/3,1/2,1/1)	(1,1,1)	(5,6,7)
S6	(1/5,1/4,1/3)	(1/7,1/6,1/5)	(1/4,1/3,1/2)	(1/9,1/8,1/7)	(1/7,1/6,1/5)	(1,1,1)
Expert 2's pairwise matrix MS^2						
DM2	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**
S1	(1,1,1)	(3,4,5)	(1,2,3)	(1/6,1/5,1/4)	(1/4,1/3,1/2)	(5,6,7)
S2	(1/5,1/4,1/3)	(1,1,1)	(1/3,1/2,1/1)	(1/8,1/7,1/6)	(1/7,1/6,1/5)	(1,2,3)
S3	(1/3,1/2,1/1)	(1,2,3)	(1,1,1)	(1/6,1/5,1/4)	(1/5,1/4,1/3)	(3,4,5)
S4	(4,5,6)	(6,7,8)	(4,5,6)	(1,1,1)	(1,2,3)	(7,8,9)
S5	(2,3,4)	(5,6,7)	(3,4,5)	(1/3,1/2,1/1)	(1,1,1)	(6,7,8)
S6	(1/7,1/6,1/5)	(1/3,1/2,1/1)	(1/5,1/4,1/3)	(1/9,1/8,1/7)	(1/8,1/7,1/6)	(1,1,1)
Expert 3's pairwise matrix MS^3						
DM3	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**
S1	(1,1,1)	(1,2,3)	(2,3,4)	(1/3,1/2,1/1)	(1/5,1/4,1/3)	(5,6,7)
S2	(1/3,1/2,1/1)	(1,1,1)	(1,2,3)	(1/4,1/3,1/2)	(1/6,1/5,1/4)	(3,4,5)
S3	(1/4,1/3,1/2)	(1/3,1/2,1/1)	(1,1,1)	(1/5,1/4,1/3)	(1/9,1/8,1/7)	(3,4,5)
S4	(1,2,3)	(2,3,4)	(3,4,5)	(1,1,1)	(1/3,1/2,1/1)	(6,7,8)
S5	(3,4,5)	(4,5,6)	(7,8,9)	(1,2,3)	(1,1,1)	(8,9,9)
S6	(1/7,1/6,1/5)	(1/5,1/4,1/3)	(1/5,1/4,1/3)	(1/8,1/7,1/6)	(1/9,1/9,1/8)	(1,1,1)

The experts' pairwise matrices for environmental barriers

Expert 1's pairwise matrix MN^1				
DM1	**N1**	**N2**	**N3**	**N4**
N1	(1,1,1)	(7,8,9)	(8,9,9)	(1,2,3)
N2	(1/9,1/8,1/7)	(1,1,1)	(1,2,3)	(1/8,1/7,1/6)
N3	(1/9,1/9,1/8)	(1/3,1/2,1/1)	(1,1,1)	(1/9,1/8,1/7)
N4	(1/3,1/2,1/1)	(6,7,8)	(7,8,9)	(1,1,1)
Expert 2's pairwise matrix MN^2				
DM2	**N1**	**N2**	**N3**	**N4**
N1	(1,1,1)	(8,9,9)	(7,8,9)	(2,3,4)
N2	(1/9,1/9,1/8)	(1,1,1)	(1/3,1/2,1/1)	(1/9,1/8,1/7)
N3	(1/9,1/8,1/7)	(1,2,3)	(1,1,1)	(1/8,1/7,1/6)
N4	(1/4,1/3,1/2)	(7,8,9)	(6,7,8)	(1,1,1)
Expert 3's pairwise matrix MN^3				
DM3	**N1**	**N2**	**N3**	**N4**
N1	(1,1,1)	(7,8,9)	(6,7,8)	(2,3,4)
N2	(1/9,1/8,1/7)	(1,1,1)	(1/3,1/2,1/1)	(1/8,1/7,1/6)
N3	(1/8,1/7,1/6)	(1,2,3)	(1,1,1)	(1/7,1/6,1/5)
N4	(1/4,1/3,1/2)	(6,7,8)	(5,6,7)	(1,1,1)

The experts' pairwise matrices for organizational barriers

Expert 1's pairwise matrix MO^1			
DM1	**O1**	**O2**	**O3**
O1	(1,1,1)	(2,3,4)	(3,4,5)
O2	(1/4,1/3,1/2)	(1,1,1)	(1,2,3)
O3	(1/5,1/4,1/3)	(1/3,1/2,1/1)	(1,1,1)
Expert 2's pairwise matrix MO^2			
DM2	**O1**	**O2**	**O3**
O1	(1,1,1)	(4,5,6)	(2,3,4)
O2	(1/6,1/5,1/4)	(1,1,1)	(1/3,1/2,1/1)
O3	(1/4,1/3,1/2)	(1,2,3)	(1,1,1)
Expert 3's pairwise matrix MO^3			
DM3	**O1**	**O2**	**O3**
O1	(1,1,1)	(1,2,3)	(2,3,4)
O2	(1/3,1/2,1/1)	(1,1,1)	(1,2,3)
O3	(1/4,1/3,1/2)	(1/3,1/2,1/1)	(1,1,1)

The experts' pairwise matrices for supply chain barriers

Expert 1's pairwise matrix MC^1				
DM1	**C1**	**C2**	**C3**	**C4**
C1	(1,1,1)	(1/6,1/5,1/4)	(1,2,3)	(4,5,6)
C2	(4,5,6)	(1,1,1)	(6,7,8)	(7,8,9)
C3	(1/3,1/2,1/1)	(1/8,1/7,1/6)	(1,1,1)	(1,2,3)
C4	(1/6,1/5,1/4)	(1/9,1/8,1/7)	(1/3,1/2,1/1)	(1,1,1)
Expert 2's pairwise matrix MC^2				
DM2	**C1**	**C2**	**C3**	**C4**
C1	(1,1,1)	(1/9,1/8,1/7)	(1/4,1/3,1/2)	(1,2,3)
C2	(7,8,9)	(1,1,1)	(6,7,8)	(7,8,9)
C3	(2,3,4)	(1/8,1/7,1/6)	(1,1,1)	(3,4,5)
C4	(1/3,1/2,1/1)	(1/9,1/8,1/7)	(1/5,1/4,1/3)	(1,1,1)
Expert 3's pairwise matrix MC^3				
DM3	**C1**	**C2**	**C3**	**C4**
C1	(1,1,1)	(1/9,1/8,1/7)	(1/8,1/7,1/6)	(1/3,1/2,1/1)
C2	(7,8,9)	(1,1,1)	(4,5,6)	(5,6,7)
C3	(6,7,8)	(1/6,1/5,1/4)	(1,1,1)	(2,3,4)
C4	(1,2,3)	(1/7,1/6,1/5)	(1/4,1/3,1/2)	(1,1,1)

B.5 The weighting of each barrier under different dimensions

T (W_T^n)	DM1	DM2	DM3
T1	0.033015	0.050256	0.021253
T2	0.348203	0.346888	0.268080
T3	0.267712	0.174347	0.373998
T4	0.165826	0.278692	0.151898
T5	0.023501	0.022263	0.034033
T6	0.104346	0.095023	0.092791
T7	0.057397	0.032531	0.057946
CR (C_T^n)	0.041872	0.062333	0.050230
E (W_E^n)	**DM1**	**DM2**	**DM3**
E1	0.102034	0.238487	0.121957
E2	0.172118	0.136500	0.558425
E3	0.725848	0.625013	0.319618
CR (C_E^n)	0.025055	0.015771	0.015771
S (W_S^n)	**DM1**	**DM2**	**DM3**
S1	0.081862	0.135785	0.147508
S2	0.157451	0.047618	0.092103
S3	0.054729	0.085539	0.060220
S4	0.414289	0.419939	0.240248
S5	0.262214	0.281121	0.433025
S6	0.029455	0.029998	0.026895
CR (C_S^n)	0.041068	0.037370	0.030477
N (W_N^n)	**DM1**	**DM2**	**DM3**
N1	0.533939	0.577738	0.570639
N2	0.067006	0.043504	0.048723
N3	0.044495	0.065513	0.074042
N4	0.354561	0.313245	0.306596
CR (C_N^n)	0.030025	0.059570	0.056942
O (W_O^n)	**DM1**	**DM2**	**DM3**
O1	0.625013	0.648329	0.539615
O2	0.238487	0.122020	0.296961
O3	0.136500	0.229651	0.163424
CR (C_O^n)	0.015771	0.003185	0.007933
C (W_C^n)	**DM1**	**DM2**	**DM3**
C1	0.190915	0.080968	0.049165
C2	0.656707	0.693314	0.629526
C3	0.098698	0.172437	0.228967
C4	0.053680	0.053280	0.092342
CR (C_C^n)	0.041909	0.074155	0.075820

B.6 Weighting of decision makers

	DM1	DM2	DM3
CR (C_D^n)	0.043268	0.029973	0.076203
CR (C_T^n)	0.041872	0.062333	0.050230
CR (C_E^n)	0.025055	0.015771	0.015771
CR (C_S^n)	0.041068	0.037370	0.030477
CR (C_N^n)	0.030025	0.059570	0.056942
CR (C_O^n)	0.015771	0.003185	0.007933
CR (C_C^n)	0.041909	0.074155	0.075820
CR (average)	0.034139	0.040337	0.044768
Weight of DM	34.693%	33.161%	32.146%