

Evaluation of strategies to manage risks in smart, sustainable Agri logistics sector: A Bayesian-based group decision-making approach

Abstract

The agriculture industry is one of India's largest and most important economic contributors. This is vital to the Indian economy since it contributes around 18% to the GDP and employs over 60% of the labour force. Due to the nature of the goods, however, this sector confronts many challenges. An effective agri-logistics network can be a viable solution, but the sector must be prepared to overcome various risks. Therefore, this study aimed to identify potential risks to the smart, sustainable agri-logistics industry and strategies for mitigating those risks. Bayesian Best Worst Method (BBWM) was used to prioritise the identified risks and the mitigating strategies. Study results indicate that by obtaining the highest ratings, technological (0.351), social (0.187), and individual (0.169) are the dominating risks to the Agri-logistics sector. Further, it was discovered that combining multiple strategies is more effective than any one strategy alone in reducing the identified risks.

Keywords: Environmental Strategies, Sustainable Agro- Logistics; Smart Logistics; Risks; BBWM

1. Introduction

The world has seen a series of disease outbreaks in the last few decades, including cholera, influenza, dengue fever, Spanish flu, Severe Acute Respiratory Syndrome (SARS), Middle East Respiratory Syndrome (MERS), Ebola and most recently, the coronavirus (COVID-19) (Kamble et al., 2020). These outbreaks have had far-reaching effects, disrupted global socioecological systems, impacted billions of people, and required massive financial resources to recover from (Sengupta, 2021). One thing they all had in common was that they exerted stress on the Agricultural Supply Chains (ASCs), resulting in a plethora of critical challenges (Coderoni & Perito, 2020). On the other hand, the increasing population has put a strain on the world's finite supplies of fresh water, land, and energy, driving up food prices and increasing market volatility (Zhu et al., 2018). Unprecedented catastrophes, such as COVID-19, represent an even greater danger to sustainable development (Alam et al., 2021). For example, it was estimated that 101 to 104.6 million additional individuals across 27 countries suffered from acute hunger due to COVID-19 (Clapp & Moseley, 2020).

To address these concerns, scientists have been identifying instabilities in ASCs and have documented the underlying environmental and political flaws in the current globalised paradigm (Bosona & Gebresenbet, 2013; Macharis et al., 2014; Raj et al., 2020). It is argued

that improving the adaptability of ASCs requires a comprehensive understanding of the interactions between risks such as obsolete technology and social ignorance (El Bilali & Allahyari, 2018; Li et al., 2019). These risks may slow or even reverse the progress of the Sustainable Development Goal (SDG) of 2030, so the assessment is crucial (APEDA, 2021). However, experts believe that the issue can be resolved if all nations adopt the concept of sustainable logistics and integrate sustainable development principles into their logistics systems (Nasr et al., 2021; Sharma et al., 2020). Sustainable logistics seeks to strike a balance between economic viability, environmental protection, and social equity to strengthen the three pillars of sustainability (Yeboah et al., 2014).

Also, because most developing and underdeveloped nations rely primarily on agriculture and food imports, effective and reliable agricultural logistics are essential (Coderoni & Perito 2020). Recent research highlighted various issues with underdeveloped nations' agri-logistics networks. It is observed that they have been struggling due to a lack of structural transformation, deficiency of management, unreliability of information, and inefficient supply chains, making them vulnerable to severe problems during unprecedented conditions such as those created by the recent pandemic (Kamble et al., 2020). Also, the quality of agricultural products degrades much more quickly than other commodities, posing a substantial challenge to agro-logistics firms (El Bilali and Allahyari, 2018; Nyamah et al., 2017). This might cause a domino effect and shift the productive status quo away from a stable equilibrium (Frittelli et al., 2019). These problems directly affect the supply and demand of essential goods and services like food and medicine, which are inextricably linked to food security. As a result, global food security is at risk (Dani, 2015; Malek & Desai, 2019; Sharma et al., 2020).

The advantages of a well-developed agro-logistics network become more apparent when comparing a developing nation like India, where 60% of the population is engaged in agriculture and contributes 18.1% to its Gross Domestic Product (GDP), to the United States, where only 10% of the population is involved in agricultural production and contributes 5% to its GDP (Arjun, 2013). Indian agro-logistics firms lack facilities like cold storage, refrigerated trucks, cool chains, ripening chambers, and vital infrastructure (Agarwal & Saxena, 2018; Nasr et al., 2021; Yadav et al., 2019). A recent survey estimated that approximately 30% to 40% of fruits and vegetables (approximately 25% of total value) are wasted due to post-harvest losses (Agri Logistics, 2021). Despite India being the world's second-largest producer of fruits and vegetables, inadequate modal mixing and pathological factors like bacterial or fungal deterioration have been identified as the primary causes of

high waste. As a result, the local population has a scarcity of fruits and vegetables and is more dependent on imports (Bung, 2017). Further, in India, a large portion of the agro-logistics sector remains unorganised, which limits the sector's accessibility to investors and impedes growth in terms of technology and the industry's ability to employ qualified and trained workers. The production and consumption zones are highly skewed in distribution; thereby, logistics companies need significant changes (e.g., technological and structural) to handle these irregularities (Canfora, 2016).

Overall, this waste of agricultural products is incompatible with the concept of sustainability in agro-logistics (Yadav et al., 2019). Also, it brings grave concern regarding equitable societal access to safe, nutritious and not-too-expensive foods. Therefore, the Government of India has been collaborating with the Department of Biotechnology and Genetic Engineering Appraisal Committee on the Aegi Reform Bill to change India from an importer of agricultural products to an efficient exporter and to enhance food security (Shukla et al., 2018). Science and technology may serve as catalysts to accelerate this development process, allowing stakeholders to generate momentum for progress and realise the goal of a self-reliant India (Agarwal & Saxena, 2018). Modern technologies such as Artificial Intelligence (AI) and Machine Learning (ML) may play a crucial role in India's transformation of the Food Supply Chains (FSC) from farm to fork (D'Antoni et al., 2012; Kittichotsawat et al., 2021; Mor et al., 2021).

Moreover, there has been a tremendous increase in demand for quick delivery in the last few years (Dablanc et al., 2017). That has spurred the development of agro-logistics sectors globally, allowing for faster infrastructure development. The development created many new jobs and supported the agricultural sector by making it a critical link between supply and demand (Badraoui et al., 2020). However, ASCs had significant difficulties amid unusual situations, such as those caused by the recent pandemic, as they were exposed to several hazards. Only a few studies have examined this topic and concentrated on the risks associated with ASCs (Raj et al., 2020; Yeboah et al., 2014). Quantitative risk management in ASCs organisations has received less attention (Long et al., 2016; Sharma et al., 2020). None of the studies has proposed a method for prioritising the risks associated with ASCs. Consequently, the following research questions (RQs) remained unanswered:

RQ1: What are the sustainability risks to smart agricultural supply chains (ASCs)?

RQ2: How can we rank and prioritise the risks to ASCs?

RQ3: What are the strategies to address the risks associated with ASCs?

In order to answer these RQs, the following objectives were proposed for this study:

- i. Identify the sustainability risks associated with smart agricultural supply chains (ASCs).*
- ii. To analyse and prioritise the risks associated with the adoption of sustainable agro-logistics.*
- iii. To develop and rank alternative risk management strategies and assess their potential effectiveness in mitigating risks associated with the adoption of sustainable agro-logistics.*

We used the Bayesian Best Worst Method (BWM) to achieve these research objectives. The study results will aid managers in recognising and prioritising risks connected with ASCs and setting strategic objectives to address them. The rest of this study is laid out as follows:

- a. Section two deals with a literature review related to risks and mitigating strategies for the smart, sustainable agro-logistics sector;
- b. Section three discusses the BBWM methodology and its steps;
- c. Section four provides the finalised risks and strategies based on the case study results and the application of BMWM to the multi-cases;
- d. Section five discusses results related to risks and strategies;
- e. Section seven summarises the study's conclusions and implications and provides suggested foci for future research.

2. Literature Review

2.1. Supply Chain Network

Supply chain operations significantly affect businesses and global commerce (Thilman et al., 2021). Customers play a crucial role in supply chain operations, and markets strive to meet their expectations by reducing lead times, improving product quality, expediting delivery, and forecasting future demands (Coderoni & Perito, 2020). However, the scarcity of essential resources, the instability of the economies, the increasing social implications, and the expanding consumer demands for high-quality products all encourage decision-makers to evaluate and build more reliable, high-quality supply chain networks (Salehi-Amiri et al., 2021). A supply chain network (SCN) is a more sophisticated version of the classic supply chain that leverages current technologies to transform it into a more complex and advanced logistical network, which can increase dependency and connectivity among businesses (Haddud et al., 2017). A SCN helps emphasise the relationships among organisations, as most companies do not operate in isolation but as part of more extensive networks of organisations (Krishnan et al., 2021). This enables stakeholders to use their businesses better

by returning, updating, remanufacturing, repairing, reusing and recycling items and materials in a multi-tiered plan, resulting in improved environmental conditions (Kittichotsatsawat et al., 2021).

Additionally, by implementing modern technologies into processes, firms can monitor the movement of information and resources across organisations and provide improved services for SCNs, lowering total transportation costs (Rajan et al., 2021). Innovation, which has been regarded as a crucial element of the success of organisations and supply chains, is frequently viewed as a collaborative endeavour. SCNs engage multiple stakeholders inside and outside of businesses in supply chain linkages, fostering improved efficiency, reliability and innovation capabilities (Krishnana et al., 2021; Osumba et al., 2021; Thilmany et al., 2021; Tsai et al., 2021).

2.2. Agricultural Supply Chains

Agriculture contributes to a country's economic value by bearing responsibility for economic growth, health, nutrition, and political issues (Pretty, 2008). The agriculture SCNs include all aspects of production, distribution, marketing, sales and services. To maintain the balance, these networks must ensure that supply and demand are reliable, high-quality, and secure for workers and consumers (Leng et al., 2018). Agriculture SCN has a significant role in seed firms, farming, grain elevators, processing, distribution, agro-product retailing, and customer service (Salah et al., 2019). Scholars have emphasised the pressing need for studies into designing, implementing, and maintaining competent, efficient, and sustainable agriculture SCNs (Malek & Desai, 2019; Sgarbossa & Russo, 2017). Recent studies have identified ways to strengthen agriculture SCNs and provided opportunities for further augmentations (Nasr et al., 2021; Sharma et al., 2020; Tsai et al., 2021).

2.3. Sustainable Agro-Logistics and Supply Chain

Recently, sustainable development has emerged as a critical component of conducting business, regardless of the kind of company (Orji et al., 2020). Researchers have been suggesting that to achieve a proper balance between economic, social, and environmental risks, responsibilities, and opportunities, businesses must transform themselves from seeing sustainability as an add-on to seeing it as an integral part of the way any work is performed (Irani & Sharif, 2016; Kamble^a, 2020; Govindan et al., 2020).

Initially, the term "sustainable development" referred to preventative agriculture and industrial processes for maintaining sustainable yields. In this regard, sustainable agriculture is a way to handle fundamental and practical food production issues in an ecologically

responsible manner. It is a set of ideas that considers both the environment and people. It requires monitoring the current rate of resource consumption to preserve the ecological balance for current and future generations and ensure profitability, environmental health, and economic and social equity. When these ideas are applied to agriculturally-focused logistics, they are called Sustainable Agro-Logistics (Kesavan & Swaminathan, 2008; Yadav et al., 2019). In 1989, the American Society of Agronomy defined sustainable agriculture as one that, over time, enhances the quality of the environment and the resource upon which it depends. It must satisfy basic human needs for food and fibre, be economically viable, and improve farmers' and society's quality of life (Bongiovanni & Lowenberg-DeBoer, 2004). The relevant literature suggests that for agriculture to be sustainable, producers and consumers must minimise the use of nonrenewable inputs in agriculture (Liu et al., 2017; Salehi-Amiri et al., 2021), integrate biological and ecological processes such as nutrient cycling and nitrogen fixation into the food production process (Chel & Kaushik, 2011), make effective use of farmers' knowledge and abilities, thus increasing their self-reliance and reducing the need for additional expensive inputs (Pretty, 2008).

It is essential to integrate these objectives into agro-logistical systems to ensure that food and other agricultural products are accessible at the right location and time while maintaining an acceptable level of quality in accordance with the three pillars of sustainability. India has set goals of achieving 500 GW of renewable energy capacity and a 35% reduction in greenhouse gas (GHG) emissions by 2030. To meet these targets, agriculture must be prioritised since it accounts for 18% of GHG emissions, and most of its equipment is powered by fossil fuels, which accelerates environmental damage (Li et al., 2017). Experts suggest that renewable resources such as solar, wind, biomass, tidal, geothermal, small-scale hydro, biofuels, and wave-generated power have huge scope in agriculture (Bung and Ison, 2020; Rajan et al., 2021). Sustainable agriculture aims to maximise agricultural yields and maintain economic stability while using as few natural resources as feasible and producing the least amount of environmental damage possible (Chel & Kaushik, 2011; Yadav et al., 2019).

This can be achieved by applying modern technologies (D'Antoni et al., 2012, El Bilali & Allahyari, 2018; Long et al., 2016). Misak et al. (2015), for example, suggested employing information technology (IT) in agricultural production to optimise inputs to attain or monitor desired outcomes. Cai et al. (2018) urged for the implementation of crop protection strategies, technologies, and solutions in order to preserve the health of ASC. The authors stressed the

need for input management based on understanding the life cycle of agricultural goods, livestock, and pests. Similarly, according to Sarrocco & Vannacciit (2018), it is crucial to adopt preventative measures in ASCs wherever possible (Lajoie-O'Malley et al., 2020). The extensive use of modern technologies is indicative of the application of contemporary crop protection agents, as these technologies enable precise soil and plant analyses and provide accurate data on external factors such as weather conditions and resource optimisation. As a result, farmers may protect their crops, increase their profits, and lessen their environmental effects. Doing so will ensure that resources are accessible for future generations while also maintaining a healthy environment, which will aid in the general development of the organisation and society (Thilmany et al., 2021). In pertinent literature, governments, corporations, farmers, and consumers need to make more informed decisions is often underlined. Also, a framework is required in order to assess the costs and benefits of social equity in different food systems, including their components, institutions, policies, and value chain (i.e. from production, processing, trade and distribution to access and consumption, including food waste management) in order to achieve the stated goal of sustainable ASC (Li et al., 2019; Liu et al., 2021).

2.4. Previous studies on Smart Sustainable Logistics and Supply Chain

Agriculture is inherently risky and unpredictable (Yeboah et al., 2014). Most risks come from the weather, climate, diseases, natural disasters, and sudden changes in the market or the environment (Sharma et al., 2020). Other threats include logistics, infrastructure, public policy, political environment, and institutions (Sgarbossa & Russo, 2012). In recent years, several threats have intensified due to climate change and fluctuating food costs (Assa et al., 2021). Practitioners have recommended cloud-based smart technologies, including AI, ML, robots, drones, and 5G, to make the sector healthier and more productive (Desai & Bohara, 2021). For instance, recent blockchain applications in agriculture aimed to improve food safety and transaction speeds (Kamble^b et al., 2020). According to Salah et al. (2019), blockchain technology, such as decentralisation and smart contracts, can weed out counterfeits in the agri-food supply chain, delivering healthier products to consumers, fostering trust between business players, and facilitating a better life in a global scale.

The work of Canfora (2016) examined the growing popularity of fast food chains in the European Union and state laws, highlighting their critical role in achieving environmental objectives. A rethinking of market performance principles and the free movement of products was considered. In a further study, Borodin et al. (2016) summarised how operations research

methods have been applied to address uncertainty in ASC management. Nevertheless, Kamble et al. (2020) emphasised that while experimental thinking can address the root causes of agricultural mismanagement, quantitative management of its operations is required for agriculture to adjust to vulnerability.

In the last two decades, executives in rural production networks have garnered great attention. This may continue, given how strict the fundamental criteria are (Dablanc et al., 2017). The companies' attention to manageability reveals the actions of farm SCNs and the characteristics of the end market, leading to key decisions about sustainability goals (Rueda et al., 2017). On top of that, there is a discussion on natural management, questioning why companies engage in such endeavours and how they pick the specific tools for actions based on their present situation (Nasr et al., 2021).

A systematic analysis by Assa et al. (2021) showed that the support strategy for the agricultural industry has a considerable exchange cost. The study demonstrated a potential area of research that can help stakeholders better understand corporate decision-making. In addition, the research suggested that an evaluation of the effect of private firms on the environmental management of agricultural regions must include a factual basis. Rakhmangulov et al. (2017) review the aspects of the sustainable development of transport framework, green coordination and the inclusion of natural elements in the act of integration. The study found that planning requires methods and norms for proper growth. Govindan et al. (2020) extended the findings of Rakhmangulov et al. (2017) by adding that in the absence of a framework for implementing green coordination strategies, the methods and tools are frequently less effective on their own and have a detrimental effect on the sustainability of the agro-logistics. Similar conceptual work was done by Hofmann et al. (2020). They offered a technique for obtaining acceptable progress targets based on harmonising financial goals and coordination norms with ASC objectives, which aids in achieving sustainable development. However, this methodology not only harmonised commonly used coordination methods but also identified places where these approaches were required by determining the goals of supportable events that are not addressed by current coordination strategies (Agrawal et al., 2022).

Recently observed benefits of digitalisation in supply chain activities have led to the conclusion that information and communication technologies (ICTs) can contribute to needed improvements in food sustainability by improving methods for envisioning and assessing effects, enacting fundamental changes, and collaborating with the current natural way (Chen et al., 2012; Verdonk, 2019). New ICT innovations and administrations can enable food

managers to demonstrate a higher level of proficiency in asset utilisation (Bosona & Gebresenbet, 2013). Further, Chenarides et al. (2021) suggested that IT helps expose food consumption patterns and actions needed to restore the natural pecking order. The roles of smart farming revolution research and development in ASC cannot be overlooked (El Bilali & Allahyari, 2018). Leng et al., (2018) found that the two-stage agricultural business asset blockchain may enable flexible lease chasing and coordination with a public assistance stage. Furthermore, it is advised to create applications and administrations that are straightforward to use, substantial, limited, and reasonable in order to optimise their advantages in natural settings and non-industrialised nations (Haddud et al., 2017). Overall, a systematic review of literature on smart, sustainable agriculture logistic systems revealed that advanced innovations, such as the implementation of IoT, AI and ML-based solutions, edge computing, 5G, robotics, and flood technologies, have the potential to reduce weaknesses and deficiencies in food supply systems (El Bilali & Allahyari, 2018; Ying et al., 2018).

On the other hand, Kamble et al. (2020) found that several exploration methods and analysis levels related to visual, profound, and prescriptive research are needed to look into the maintainability problems in the agri-food Supply Chain (AFSC). The study revealed that an unprecedented level of supply chain visibility (SCV) and association coordination is necessary for the practical implementation of advanced innovations. The findings showed that SCV and inventory network assets are the predecessors of data analytics capacity that lead to sustainable network execution. In brief, it is suggested that the association's data collection system should serve as the basis for AFSC verification. According to Sharma et al. (2020), the solution is neither simple nor easy to implement. They highlighted the risks agricultural SCNs in India faced during the COVID-19 pandemic. The prominent risks were categorised into four groups: miniature, small, medium, and international enterprises, and were analysed using the Fuzzy Linguistic Quantifier Order Weighted Aggregation (FLQOWA) technique. It was found that supply risks, demand risks, monetary risks, coordination and framework risks, board and operational risks, arrangement and policy risks, and natural and environmental risks significantly impact the different organisations, depending on their size and scope. Many methods for reducing risks and impacts, as well as for tracking the paths towards the new normal, including rapid changes, selection of industry 4.0 breakthroughs, coordinated efforts and shared accountability for a sustainable future, were suggested in the relevant literature. However, a closer examination of the literature revealed several gaps and deficiencies, which are discussed in the following section.

2.6. Research Gap and Highlights

The preceding literature analysis demonstrates that many studies have been conducted in sustainable logistics and ASC, individually and in collaboration. Among other, an important comprehensive study was conducted by Yeboah et al. (2014) on identifying agricultural risks and classifying them according to their severity. Canfora (2016) researched the increasing popularity of shorter food chains in the European Union in view of their essential importance in attaining environmental goals. Similarly, in their review, Sharma et al. (2020) identified and examined the effects of hazards on the Indian ASC linkages during the COVID-19 pandemic. Additionally, Bilali and Allahyari (2018) emphasised the need for radical changes to the food supply chain in order to make it more affordable, and proposed the use of ICTs as a viable solution to the issue. Moreover, Borodin et al. (2016) summarised how operations research methods can be applied to address uncertainties in ASC management.

The reviewed literature offered no precise methods for reducing the risks associated with sustainable agro- logistics and the strategies for dealing with them. There seems to be no widely recognised answer(s) to the problem of sustainable logistics in the ASCs. Much work still has to be done to solve the problem of environmental legislation on logistics businesses that are being enforced by governments since increasing carbon footprints are linked with conventional logistics techniques (Van Loon et al., 2015). A better knowledge of risks is needed to improve enterprises' competitiveness in the agricultural industry by using cutting-edge technologies.

According to expert opinion in pertinent literature, sustainable logistics (reduced environmental impact) will ultimately replace conventional logistics in the ASCs in the not-too-distant future. As a result of seeing this as an opportunity for agriculture, the authors of this paper examined the risks that may block its acceptance and sought to develop the appropriate strategy to address them. We are particularly interested in creating a framework that will assist shareholders in managing different risks using suitable strategies and technologies. Our study focused mainly on the risks of emerging nations such as India, where the problem of adopting ecologically friendly technologies is a major obstacle.

3. Research Methodology

This study employs a two-phase, multiple-case methodology (see Figure A) to identify and rank risks and their mitigation strategies in the smart and sustainable agro-logistics sector. A case study approach is used because it helps examine a contemporary phenomenon in detail and its actual context (Yin, 2013). Here, the multi-case approach is used since many experts

with diverse industry backgrounds participated in the data collecting (Gupta et al., 2020; Kusi-Sarpong et al., 2021). This multi-case study focuses on the agro-logistics sector in India. Here the agro-logistic sector was considered because it is one of the largest emerging sectors in this country and the world, and it ranks ninth in total global exports (Kumar & Kumar Singh 2022). The present growth rate of the logistics sector is expected to be 23,044 USD billion in the next five years. In addition, this sector has a 2.1% contribution to India's global trade.

3.1. Case application

This multi-case analysis study was done with the help of 12 experts from different agro-logistics organisations (*See* table 1). The experts came from a heterogeneous and not homogenous group, resulting in a diverse set of inputs; hence, the sample size for this multi-case analysis is enough (Dodd & Yengin, 2021). Because diversity aids researchers in comprehending the complexities and intricacies of social interactions, it has been regarded as a way for improving the external validity or generalizability of study framework (Merriam, 1998; Nguyen et al., 2019). The framework is comprised of three phases, as shown in Figure A and described in detail below:

3.2.1 Phase 1: Identification of risk and overcoming strategy

This phase comprises two steps – identification of risks and strategies, respectively. In detail the steps are discussed below.

Step 1: Identification of risks

In this step, the Modified Delphi techniques (Gupta et al., 2020), we first perform an extensive literature review, tabulated and presented the identified risk to the experts. After that, a group discussion was held via zoom. In addition, twenty associated risks were finalised and classified into four categories, namely technological, social, regulations and institutional, individual, and environmental. The finalised list of risks is shown in Table 2.

Step 2: Identification of overcoming strategies

Similarly, using the Modified Delphi techniques (Gupta et al., 2020), as discussed earlier, we conducted an extensive literature review and tabulated and presented the list of overcoming strategies to experts. Again, after several rounds of group discussion, eight overcoming strategies were considered. The finalised overcoming strategies for ASC risks are presented in Table 3.

3.2.2 Phase 2: Analysis and ranking of risks

This phase involves the application of the Bayesian best-worst method (BBWM) to prioritise sustainability risks associated with the sector. The risks are rated as per their weights obtained from BBWM, and overcoming techniques are scored using a combination of these weights and the score of each strategy.

The Bayesian BWM method is a vital and powerful tool when considering the multi-case approach and ranking weights in a probabilistic sense. Here, each identified risk is quite complex and not similar to others. Several case companies and different experts' opinions are considered in this case. As multiple case companies are considered here, therefore, for analysis of the risk and their overcoming strategy, a multi-case approach with BBWM is considered for further analysis (Gupta et al., 2022). BBWM is used here because it considers multi-nominal distributions during pairwise comparisons (Mohammadi & Rezaei, 2020). Several studies used BBWM methods with a multi-case approach in different domains, like barrier prioritisation in supply chain logistics (Gupta et al., 2022), health safety and risk calculation (AK et al., 2022), risk measurement (Zhang et al., 2022), in blockchain technology (Liu et al., 2021), marketing (Zhang et al., 2022), and in operation research (Wang & Rezaei, 2020).

As stated before, BBWM was utilised to prioritise risks to the sustainability of ASC operations. The basic BWM is related to the Analytical Hierarchy Process (AHP) in that it employs the same 9-point scale for pairwise comparisons among the criteria and for the computation of criteria weights, both of which are used in the AHP. However, BWM first determines the best and worst criteria among a collection of criteria and then requires comparisons between the best and worst criteria and between the best and worst criteria and the remainder of the options. Additionally, it outperforms AHP because it produces consistent results with fewer pairwise comparisons (Rezaei, 2015). BWM has grown in popularity among academics worldwide, and many researchers are incorporating it into their work. Some important applications of BWM include Gupta & Barua (2017) (for green innovation supplier selection), Kheybari et al. (2019) (for bioethanol facility selection), Malek & Desai (2019) (for sustainable manufacturing barriers prioritisation), Yadav et al. (2019) (for smart cities framework evaluation); Govindan et al. (2020) (for barriers to industrial sharing economy analysis); Kaushik et al., (2020) (for online apparel return factors analysis), Orji et al., 2020 (for the analysis of social media success factors for sustainability), and, Gupta et al., 2020 (for the analysis of barriers and overcoming strategies to supply chains sustainability innovation). Mohammadi & Rezaei (2020) suggested BBWM as a method for calculating

group weights based on statistical probability distributions. The stages involved in BWM are given in Figure A.

Insert Figure A Here

Figure A. Research framework to identify and assess risk management techniques in the smart, sustainable Agri logistics

The steps of BBWM are as follows

Step 1: Select relevant criteria for the study

Step 2: Once the criteria are finalised, choose amongst the main and sub-criteria the Best and Worst criteria.

Step 3: The next step is to develop a rating of the best criterion among all criteria. For this purpose, a scale of 1 to 9 can be used. This will result in vector $A_B = (a_{B1}, a_{B2}, \dots, a_{Bn})$.

Step 4: Similarly, the next step is to develop a rating of all other criteria with worst criterion. All the experts are required to follow steps 3 and 4. This will also result in vector $A_W = (a_{1W}, a_{2W}, \dots, a_{nW})^T$.

Step 5: Next, it is necessary to obtain the optimised weights $(w_1^*, w_2^*, \dots, w_n^*)$ for all the criteria.

The A_B and A_W Vectors can then be converted into a multinomial probability distribution.

The $P(A_W|w)$ represents the probability mass density function of A_W

$$P(A_W|w) = \frac{(\sum_{j=1}^n a_{jw})!}{\prod_{j=1}^n a_{jw}!} \prod_{j=1}^n w_j^{a_{jw}} \quad (1)$$

w indicates probability distribution. The probability of multinomial distribution is influenced by the number of experiments for even j .

$$w_j \propto \frac{a_{jw}}{\sum_{i=1}^n a_{iw}} \quad \forall j = 1, \dots, n. \quad (2)$$

The equation for the worst criterion will be

$$w_W \propto \frac{a_{WW}}{\sum_{i=1}^n a_{iw}} = \frac{1}{\sum_{i=1}^n a_{iw}} \quad (3)$$

Combining equations (2) and (3), one can obtain the following

$$\frac{w_j}{w_W} \propto a_{jw}, \quad \forall j = 1, \dots, n. \quad (4)$$

Equation (4) is similar to the concept followed in the original BWM.

As stated above, the vector A_B can be modeled in the same manner. Since A_B is representing the best of all, so it can be denoted as the inverse of the earlier weight as follows:

$$A_B \sim \text{multinomial}(1/w) \quad (5)$$

Which can be further written as

$$\begin{aligned} \frac{1}{w_j} &\propto \frac{a_{Bj}}{\sum_{i=1}^n a_{Bi}}, & \frac{1}{w_B} &\propto \frac{a_{BB}}{\sum_{i=1}^n a_{Bi}} = \frac{1}{\sum_{i=1}^n a_{Bi}} \\ \Rightarrow \frac{w_B}{w_j} &\propto a_{Bj}, & \forall j &= 1, \dots, n, \end{aligned} \quad (6)$$

The Dirichlet statistical distribution can be used to determine the weight vector. The weight vector has the property of a sum equal to 1. It is mentioned below

$$Dir(w|\alpha) = \frac{1}{B(\alpha)} \prod_{j=1}^n w_j^{\alpha_j - 1} \quad (7)$$

Next, BBWM is used instead of the maximum likelihood method for approximating the parameters. The posterior distribution model can be represented below

$$\begin{aligned} \mu_j &= \frac{\alpha_{postj} - 1}{\sum_{i=1}^n \alpha_{posti} - n} \\ &= \frac{1 + a_{jw} - 1}{\sum_{i=1}^n (a_{iw} + 1) - n} \\ &= \frac{a_{jw}}{\sum_{i=1}^n a_{iw}}, \quad \forall j = 1, \dots, n. \end{aligned} \quad (8)$$

For the purpose of group decision-making, the joint probability distribution for vectors A_B and A_W must be determined.

The joint probability distribution for group decision-making can be represented below; here, we are considering k decision-makers and n criteria.

$$P(w^{agg}, w^{1:K} | A_B^{1:K}, A_W^{1:K}) \quad (9)$$

The following marginal probability rule can be used to obtain the individual probability of any arbitrary variables x and y as

$$P(x) = \sum_y P(x, y) \quad (10)$$

Next, a Bayesian model is developed considering the conditional independence among the factors; the model is mentioned below

$$\begin{aligned} P(w^{agg}, w^{1:K} | A_B^{1:K}, A_W^{1:K}) &\propto P(A_B^{1:K}, A_W^{1:K} | w^{agg}, w^{1:K}) P(w^{agg}, w^{1:K}) \\ &= P(w^{agg}) \prod_{k=1}^K P(A_W^k | w^k) P(A_B^k | w^k) P(w^k | w^{agg}) \end{aligned} \quad (11)$$

Next, we specify the distributions of each element. The above elements can also be specified as multinomial distribution as per the inferences drawn in equations (2) –(8).

$$A_B^k | w^k \sim \text{multinomial}(1/w^k), \quad \forall k = 1, \dots, K,$$

$$A_W^k | w^k \sim \text{multinomial}(w^k), \quad \forall k = 1, \dots, K. \quad (12)$$

Here, w^k and w^{agg} can be modelled as Dirichlet distribution as

$$w^k | w^{agg} \sim Dir(\gamma \times w^{agg}), \quad \forall k = 1, \dots, K, \quad (13)$$

Where w^{agg} is the average of the distribution, and γ is the concentration parameter.

The non-negativity constraints are satisfied by modeling the concentration parameters using the gamma distribution

$$\gamma \sim \text{gamma}(a, b) \quad (14)$$

Finally, Dirichlet distribution is used to model optimal weight w^{agg} as

$$w^{agg} \sim \text{Dir}(\alpha) \quad (15)$$

Here $\alpha = 1$

After that, the next step is to obtain the optimal group weight w^{agg} using Markov Chain Monte Carlo (MCMC) simulation.

The next step is ranking the confidence test. Here, Credal ranking is used to determine the confidence of consistency of group weights. Thus, the probability that a criterion c_i is better than c_j will be:

$$P(c_i > c_j) = \int I(w_i^{agg} > w_j^{agg})P(w^{agg}) \quad (16)$$

Here, $P(w^{agg})$ is the posterior distribution of w^{agg} . I will be 1 if the condition ($w_i^{agg} > w_j^{agg}$) holds; otherwise, it will be 0. Q samples obtained by MCMC will be used for calculating the confidence as

$$P(c_i > c_j) = \frac{1}{Q} \sum_{q=1}^Q I(w_i^{aggq} > w_j^{aggq})$$

$$P(c_j > c_i) = \frac{1}{Q} \sum_{q=1}^Q I(w_j^{aggq} > w_i^{aggq}) \quad (17)$$

Where, q^{th} sample of w^{agg} obtained from MCMC is represented as w^{aggq} . When $P(c_i > c_j) > 0.5$, it represents that criterion i is more significant than criterion j , and the confidence is represented by the corresponding probability. Also, the total probability should be equal to 1, i.e., $P(c_i > c_j) + P(c_j > c_i) = 1$.

The additive value function given by (Keeney and Raiffa, 1976) is used to evaluate alternatives.

$$V_i = \sum_{j=1}^n w_j n_{ij}. \quad (18)$$

Where i is representative of the alternative, the value of n_{ij} can be calculated by using expressions (19) and (20). Here, n_{ij} represents a normalised score. Equation (19) is used when the criteria value is supposed to increase, and we labelled it as a profit or as a positive

criterion and equation (20) is used when the criteria weights are supposed to decrease, and it is labelled as a cost or a negative criterion.

$$n_{ij} = \frac{y_{ij}}{\sum_i y_{ij}} \text{ for all } j \quad (19)$$

$$n_{ij} = \frac{\frac{1}{y_{ij}}}{\sum_i \frac{1}{y_{ij}}} \text{ for all } j \quad (20)$$

Where y_{ij} represents the value obtained of any alternative i with respect to criterion j .

3.2.3. Phase 3: Analysis and ranking of overcoming strategies

This phase comprises the evaluation of strategies to help identify the pathway to helping avoid and overcome the risk in smart sustainable ASC. All the finalised twenty risks were ranked with respect to each main category and subcategory risk. Again, all twelve experts were asked to rate each strategy which respects the main category strategy on a 1-to-9-point linguistic scale. Here, 1 means less important, and 9 means very high importance. The weighted value is obtained here using equation 19 because we are considering benefit criteria and the value we want to increase.

Further from the obtained weight, we calculate the rank (see Table 6). In the same way, the ranking of all individual subcategories was also calculated. The combined weight and their rank of main category and subcategory are presented in Table 6.

4. Empirical Application

4.1. Risks and strategies based on the case study and literature review

Twelve specialists from seven companies were selected to perform the research to achieve the study goals. They were intentionally chosen from a variety of backgrounds in order to achieve consistency and to ensure that the results are more general and can be applied across industries. The experts selected for the study have a variety of profiles and work experiences (minimum of 10 years) from different organisations and industries. The studies that have been considered were referred by professionals with more than a decade of expertise in the relevant industry (for example, (Gupta et al., 2020; Kusi-Sarpong et al., 2021; Moktadir et al., 2020)). They were considered since they had evolved into middle-level and upper-level management employees. In addition to their vast experience, they have a profound knowledge of their specialised field. Table 1 provides detailed information about the twelve chosen experts.

Table 1. Details of experts and case companies

Insert Table 1 Here

The risks identified from an extensive literature review were categorised in this phase. Initially, we identified 23 risks, which were later reduced to 20 based on expert recommendations. All risks were then classified into five wider groups based on their relevance to pertinent literature. Table 2 lists the five major categories along with their sub-risks.

Table 2. Risks in smart sustainable agricultural supply chain

Insert Table 2 Here

While improved sustainability in the logistics industry has potentially huge beneficial effects, it is confronted with numerous risks, as described in the preceding sections. It is, therefore, imperative to develop ways to address these risks. Also, each risk is unique and may require more than one strategy. Based on extent review of pertinent literature, a list of all possible strategies for overcoming these risks was prepared as presented in Table 3. A total of eight potential strategies were identified to reduce the impact of potential threats to the ASC.

Table 3. Strategies for overcoming agricultural supply chain risks

Insert Table 3 Here

4.2 BBWM application to the multi-cases

Once risks and strategies were identified, the next step was to prioritise the risks. All experts were asked to assess the best and worst risks from the main categories and subcategories using Bayesian BWM. Then, on a scale of 1–9, the experts were asked to rate each of the main category and subcategory risks in terms of best-to-others and worst-to-others. Table 4 summarises the ratings for pairwise comparisons of the main category risks received from each of the twelve experts. The ratings for pairwise comparisons of all the subcategory risks are given in Appendix A (Table A1–A5).

Table 4. Pairwise comparison for main category risks

Insert Table 4 Here

After this, the weights of all the main category and subcategory risks were calculated using their pairwise ratings. The weights and the rankings for subcategory risks are presented in Table 5.

Table 5. Criteria weights and ranking of the risks

Insert Table 5 Here

The global weight for each subcategory risk in Table 5 was calculated by multiplying the local weight of that subcategory risk and the weight of its parent main category risk. After getting the weights of the subcategory risks, the next step was to find the strategies that are needed to tackle these risks. At first, all eight strategies were analysed for each of the main category risks and then for subcategory risks. All the experts were requested to give a rating for each strategy for the main category risks using a scale of 1 – 9 (see Table A6 in Appendix for the rating given by expert 1 for the strategy of main category risks), where 1 represents very less effective, and 9 represents very highly effective. All experts' mean ratings were calculated using Eq. (19), the normalised value of the scores, by which n_{ij} was determined. Then, the obtained normalised value u_{ij} was multiplied with individual weights of the main category risks to get R_i values for each strategy using Eq. (18). These R_i values signify the ranking of strategies for the main category risks, which are listed in Table 6. Likewise, the rankings of the strategies for individual subcategory risks were found using the earlier discussed steps. Table 6 provides the R_i values and rankings of all strategies for the main category and subcategory risks.

Table 6. Rankings of strategies

Insert Table 6 Here

5. Discussion of Results

5.1. The Results

In the traditional BWM method, we used two criteria to determine superiority in terms of confidence. In contrast, in the Bayesian BWM method, we introduced the concept of credal ranking, which provides us with the confidence value for all credal rankings. When this principle was applied to a real-world scenario, it was possible to determine which criteria have the highest degree of confidence among the different criteria pairs.

From figure 1, it is clear that "Technological Risks" was believed to be dominant among the main criteria risks. This was because technologies play important roles in the implementation of sustainable logistics. Although "Technological Risks" is more significant than the other four criteria, a confidence score of 1 between it and "Social Risks" indicates that all of the experts believed that "Social Risks" are more significant. Aside from that, all experts believed technological risks are more important than the other three, with a confidence level of 1. Similarly, while "Individual Risks" were deemed to be more significant than "Regulatory Risks" and "Environmental Risks," a confidence interval of 0.55 between

"Individual Risks" and "Regulatory Risks" indicated that some experts believed that "Regulatory Risks" are more significant than "Individual Risks." All the other sub-criteria credal rankings with confidence values are shown in Figures 2, 3, 4, 5, and 6.

Insert Figures 1 to 6 Here

Figures 1 to 6 represent the Confidence Level of the main and Subcategories

5.2 Discussing the risks and strategies

Following a thorough review of the literature, this study identifies various risks to the agricultural supply chain and strategies for mitigating those risks. Then these risks and strategies were analysed separately using Indian industrial experts' input. The result obtained from the inputs using the Bayesian BWM methodology is presented in Table 5. It was determined that "Technological Risks" (TR) were the biggest barrier to adopting Sustainable Logistics for agricultural supply chains within India's agriculture sector. Technological support is essential for achieving long-term success in any field, and technological development is the driving force behind any advancement. However, the costs of technologies and products for agri-ology are very high, and sustainable technology alternatives are required Li et al. (2019). Second on the list were the "Social Risks" (SR), which many organisations in developing countries face. Those risks are social risks, such as deterioration in farm product quality, unsafe road infrastructure, risks related to human health, and unpredictable events such as strikes, pandemics, etc. Due to the high number of road accidents in many developing countries, the road infrastructure is unsuitable for a sustainable agricultural supply chain in many of those countries (Gray, 2020). The third most challenging risk was the "individual risk" (IR), mainly linked to individual risks facing persons involved in the ASC. Transactional costs are high in the ASC and the logistics networks due to the large number of intermediaries, which increases overall product costs. Thus, making it unsustainable in the long run (Kamble et al., 2020).

Another problem was that people resisted changing the working practices of traditional ASC practices that influence sustainable practices (Raj et al., 2020). Among the subcategories of risk, "Cost of technology" (TR3) emerged as the most critical risk for Sustainable Logistics in the ASC. It is common for developing countries to experience high technology prices as a result of economic conditions in the country. Therefore, adopting sustainable agri-logistics alternatives can be the solution (Li et al., 2019). "Scarcity of technologically skilled farmers" (TR2) is the next significant sub-risk a developing country

must address on its path to implementing Sustainable Logistics in its ASC. Organisations in these countries have a scarcity of technologically skilled labour and require adequate training and guidance to increase manpower capable of operating technological equipment. The third most perilous sub-risk was "dangerous road infrastructure" (SR2). There is a lack of proper road infrastructure in many countries necessary for the timely delivery of good quality agricultural products. In many developing countries, road infrastructure is unsuitable for sustainable ASCs, as there are many accidents (Badraoui et al., 2020). Fourth on the list was the "Different visions of changing the government" (RR3). Due to unstable and changing governments, the degree of emphasis on sustainable logistics varies.

The study and analysis of strategies for mitigating risks associated with the adoption of sustainable logistics in ASCs demonstrate that no single strategy is capable of mitigating these risks, and the closeness of the total weighted score for these strategies (see Table 6 for values) demonstrated that multiple strategies have a significant impact on a single risk. When it comes to mitigating the overall major risks (main category risks), "Preparation for cyclic natural disaster strategy" (S8) emerges as the most effective strategy. "Preparation for cyclic natural disaster strategy" (S8) can be the most effective strategy because, in the event of a cyclic natural disaster, all technological equipment is disrupted, and the entire supply chain ceases to function. As climate change becomes more severe, a major rise in the frequency and intensity of many kinds of storms is noticed worldwide. This is consistent with Petrova's (2020) findings that Russia's transportation infrastructure is susceptible to various natural hazards and meteorological occurrences. To address "Technological Risks," the most effective strategy appears to be "Reducing the cost of technology in agriculture" (S5). For a developing country like India, the cost of technology for sustainable logistics is the most challenging obstacle to overcome. The strong agreement between the results and the literature (D'Antoni & Mishra, 2012) indicates that Indian cotton producers experienced high profits only when technological risk was minimised by precision agriculture.

Additionally, the authors noted that autosteer adoption could considerably impact farmers' perceptions of precision agriculture's future importance and their ranking of input cost reductions relative to other GPS technology qualities. The second most effective strategy on the list is "Developing technologically skilled agricultural manpower" (S4). As more sustainable technologies are adopted, the number of people required to operate and maintain those technologies will increase. This has been identified as a major issue and can be resolved if adequate training and awareness are provided to the agricultural workforce. A similar pattern of findings was obtained in the research of Erickson et al. (2018), where authors

stressed the relevance of agricultural personnel's knowledge, skills, and abilities (KSAs). KSAs have been found to improve the performance of equipment operators, sales specialists, technical support personnel, and agronomists. The study also examined the ability to install, calibrate, troubleshoot, and repair equipment; comprehension of precision agricultural software; and general qualities such as excellent written and verbal communication and the ability to make agronomy recommendations.

"Well-connected modes of transport strategy" (S6) is the most important strategy to overcome the "Social risk" (SR). In developing countries, a lack of adequately connected road infrastructure results in increased freight time and significant loss of perishable goods. Proper and well-connected road infrastructure will therefore help to solve these problems. This reasoning is aligned with Budd & Ison's (2020) recent results, which emphasise the role of the individual as a responsible, autonomous agent in providing socially desirable transportation outcomes. The second most important strategy is the "Food wastage reduction strategy" (S1). It is critical because, in a country like India, where hunger and malnutrition are major problems, food waste is a crime that occurs in large quantities. As a result, appropriate countermeasures such as increasing cold storage capacity are required. To overcome the "Regulating and Institutional Risks" (RR), the most important strategy is the "Food wastage reduction strategy" (S1). The primary issue that any agro-logistics company faces is food waste, which puts them on the government's radar; thus, increasing cold storage and refrigerated vans, among other things, can help them eliminate it. Desai & Bohara (2021) have echoed similar findings more recently. The second most effective strategy was the "Reducing carbon footprints strategy" (S2). The strategy is to reduce carbon footprints throughout a product's life cycle by employing more environmentally friendly packaging techniques, modes of transportation, processing, and storage, among other things, thereby shifting to a more sustainable agro logistics system, as described above. Therefore, the findings are consistent with the recent findings of Mor et al. (2021), in which they stressed the need for artificial intelligence (AI) technology in the Indian agricultural sector to minimise carbon emissions from farming operations and rejuvenate the whole economy. The most important strategy for overcoming "Individual Risks" (IR) is a "Well-connected modes of transport strategy" (S6).

The goal is to combine one mode of transportation with another to reduce the supply chain's lead time and delivery time and to improve the quality and sustainability of current supply chain networks (Budd & Ison (2020)). The second most effective strategy is "Creating awareness among the farmers about the bright prospect of change" (S7). This strategy is

intended to sensitise farmers on the benefits of sustainability and how they can enhance overall productivity by achieving sustainable objectives (Erickson et al., 2018). The most successful technique to combat "Environmental Risks" (ER) is the "Food waste reduction strategy" (S1). In several countries, including Sweden, Norway, Germany, the Netherlands, and Italy, "spoiled food" is utilised strategically to create bio-gas (methane) and chemicals used as a "fertiliser-soil conditioner" in agricultural and horticultural settings. It helps boost the overall system's effectiveness and the agricultural land's yield. This strategy will aid in reducing emissions from rotten farming products and the consumption of these products, which may be harmful to human health. The second most important strategy is the "Reducing carbon footprints strategy" (S2). This strategy aims to reduce carbon footprints through the use of more eco-friendly logistics techniques such as electric vehicles and also through the use of renewable products for packaging and other purposes. These results are in complete agreement with previous studies (Krishnan et al., 2021; Mor et al., 2021)

6. Conclusions

6.1 Conclusions and Implications

Adopting cutting-edge technologies is critical in today's industrial environment. As the backbone of every company, it is critical to ensure the logistics sector's sustainability. This research contributes to the existing body of knowledge by addressing the three questions at the bottom of the introduction. In response to RQ1, five main categories of risks are identified, with twenty subcategories. In order to provide an answer to RQ2, the identified risks were ranked from 1 (most severe) to 20 (least severe) using the weight derived from BBWM. This study recommends that technical, social, and individual risks (ranked 1, 2, and 3) must be prioritised for agricultural supply networks to be sustainable. In response to RQ3, a total of eight risk mitigation strategies for smart, sustainable agri-logistics sectors were identified. A single strategy may not be adequate to control risk, and it may be necessary to use multiple strategies, either directly or indirectly, as recommended by the research.

As such, it is critical to rank the strategies according to their potential effectiveness in addressing various risks. In the current context of a developing country, the most critical risks are technological, social, and individual, which require immediate attention from organisations and governing bodies. Many strategies can be used to mitigate these risks, such as preparation for cyclic natural disasters in the region, which can aid in mitigating many risks associated with sustainable logistics for the agricultural supply chain. However, the government or policymakers must provide financial incentives to encourage this strategy. It

should also promote new technologies if their costs in the agricultural sector can be reduced. Additionally, there is a need to create technologically competent agricultural personnel to ensure that such technologies are handled correctly and that the advantages of technology are reaped without reluctance.

This research has important implications for academia and industries that are directly involved in agro-logistics or are in some way reliant on logistics, which is the case for the vast majority of them. Environmental degradation due to high vehicle traffic to meet supply chain demands is always a topic of discussion. Thus, businesses must strike a balance between environmental impacts and individual growth, enabling them to remain competitive in the long run. To find this balance, companies can adopt the concept of sustainable logistics. However, the adoption process is not as easy as it appears, and there are numerous risks to consider along the way, all of which must be addressed with care. In this paper, the authors identified twenty risks to the sustainability of agricultural supply chain logistics in a developing economy's logistics sector. The framework gives a step-by-step method for identifying essential elements, rating, and mapping of methods, which may be regarded a novel contribution to the field's current theory.

The logistics sectors of these economies can work on mitigating the identified risks in order to emerge as innovative and environmentally friendly. The study identified 'technology costs', 'scarcity of technologically skilled farmers', and 'unsafe road infrastructure' as significant barriers to adopting sustainable logistics in agriculture supply chains. The study suggest government and various organisations can collaborate to bring the cost of technologies down to a more reasonable level in the region. A separate institutional structure needs to be established for sustainable technology, which can control the functioning of these technologies. This study also identified and ranked strategies for mitigating these risks. The rating was done for the methods for dealing separately with each type of risk, which may assist logistics firms in identifying the risks they face and how to tackle them. In the broader sense, businesses must devote more resources to research and development to lower the technology cost required to adopt sustainable logistics in their sector. The government's involvement in all aspects of the process is critical, and it should offer incentives and other forms of assistance to promote it.

6.2 Limitations and future scope

As with any study, this one has limitations. This study focused on risks associated with adopting sustainable logistics for agricultural supply chains, but there are also risks related to

economic issues. Future research can concentrate on the financial aspects of agriculture supply chain sustainability. This study identified twenty risks and classified them into five broad categories, but this topic can be explored further through a more comprehensive review of the literature. While this study utilised the Bayesian Best Worst Method (BBWM) to rank risks and select optimal strategies, future research may employ techniques such as the Fuzzy Best Worst Method (FBWM), which simulates real-world situations by taking into account the decision maker's confusion. This technique utilised twelve experts, which can be expanded to include specialists from various professions. Without a doubt, this exploratory study opens the door to additional possibilities for future research to be conducted.

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Consent to Participate – Not Applicable

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TABLES

Table 1. Details of experts and case companies

Expert	Expertise	Experience	Educational Background	Industry/Organisation
Expert 1	Manager- Operations	11	MBA	Food Marketing
Expert 2	Asst. Manager- Operations	10	MBA	Logistics
Expert 3	Data Scientist	11	M.Tech	Data Analysis
Expert 4	Deputy Manager- Operations	10	B.E.	Logistics
Expert 5	Manager- Operations	12	MBA	SCM
Expert 6	Asst. Manager- Process Control	10	B.Tech.	Consultancy
Expert 7	Manager- Operations	11	M.Tech	Food Marketing
Expert 8	Analyst	12	M.Tech	Consultancy
Expert 9	Manager - Logistics and Supply Chain Management	11	MBA	Logistics
Expert 10	General Manager - Logistics and SCM	23	MBA	Logistics
Expert 11	Senior Manager - Procurement	13	B.Tech.	Food Marketing
Expert 12	Manager - Technology Management	12	B.Tech.	Logistics

Table 2. Risks in smart sustainable agricultural supply chain

Major dimensions of Risk	Risk Source	Description	References
Technological (TR)	Machine, equipment or facility failure (TR1)	Any disruption caused by a mechanical failure can potentially disrupt the entire agricultural supply chain, compromising sustainable logistics.	Desai et al., 2021; Govindan et al., 2020; Li et al., 2019
	Scarcity of technologically skilled farmers (TR2)	Many villagers in developing countries such as India are unaware of the most advanced sustainable agricultural logistics technologies.	
	Cost of technology (TR3)	Technology and product costs for agrological are very high, and sustainable alternatives must be developed.	

	Use of redundant technology (TR4)	Certain technologies are not long-term viable and do not provide a positive return on investment; therefore, identifying those technologies for logistics is a risk.	
Social (SR)	Deterioration in quality of agricultural products (SR1)	The quality of agricultural products during long travel is impaired because the necessary cold storage is unavailable, and therefore, the sustainable logistics system is adversely affected	
	Unsafe road infrastructure (SR2)	In many developing countries, the road infrastructure is unsuitable for a sustainable agricultural supply chain because the number of accidents is relatively high.	Badraoui et al., 2020; Gray, 2020
	Human health-related risk (SR3)	Due to the lengthy freight time, harmful chemicals are used to keep food fresh for an extended period, eroding the concept of sustainability.	
	Unpredicted events like strikes, pandemics etc. (SR4)	Any strike or pandemic may disturb the entire supply chain network, including the logistics sector, such as the Indian farmers' strike in Dec 2020 and COVID'19.	
Regulatory & Institutional (RR)	Uncertain legal policies and enforcements (RR1)	Acceptable guidelines and regulations do not support laws enforcing sustainable agricultural and logistics technologies.	Verdonk, 2019
	Different visions of changing government (RR2)	Due to an unstable and changing government, the emphasis on sustainable logistics varies.	
	Delays in accessing financial support (RR3)	Despite funding for sustainable agricultural logistics, promptly providing this support for appropriate use is a significant issue.	Long et al., 2016; Nyamah et al., 2017; Yi et al., 2021
	Restrictions to transportation due to local issues (RR4)	There are numerous regulations, restrictions, and local concerns pertaining to sustainable agricultural product transportation.	Badraoui et al., 2020; Gray, 2020
Individual (IR)	Inadequate price for the produce (IR1)	Farmers face the risk of not receiving the best price for their agricultural produce due to supply and demand imbalances caused primarily by inefficient and unsustainable logistics networks.	
	Heavy transaction costs (IR2)	In the supply chain and the logistics networks, the transaction costs are high because a large number of intermediaries increases the overall cost of the product. As a result, it is unsustainable in the long run.	Hofmann et al., 2018; Kamble et al., 2020; Ying et al., 2018
	Resistance to change (IR3)	People resist changing their ways of working with traditional agricultural supply chain practices, which impact sustainability practices.	Haddud et al., 2017; Raj et al., 2020
	Decrease in farming manpower (IR4)	A farmer does not want his child to be involved in agriculture; consequently, the workforce required for sustainable agro logistics continues to decline.	

Environmental (ER)	Issue of carbon footprints (ER1)	Overall, carbon emissions during the product life cycle, from production to distribution, disrupt the sustainability of agro logistics.	Ackerman and Azzaro-Pantel, 2017; Kamble et al., 2020; Liu et al., 2021; Miranda-
	Wastage of food (ER2)	A significant amount of food is wasted during the agro-logistics process, negatively affecting sustainable development.	Irani and Sharif, 2016; Kamble et al., 2020; Sgarbossa and Russo, 2017
	Food quality and security (ER3)	Rising population, climate change, soil erosion, water scarcity, etc., food quality and sustainability are major concerns.	Irani and Sharif, 2016; Kamble et al., 2020
	Cyclic natural disaster (ER4)	Natural disasters that occur on a cyclical basis, such as floods and cyclones, disrupt the entire agricultural supply chain, compromising sustainable logistics.	

Table 3. Strategies for overcoming agricultural supply chain risks

Strategies	Description
Food wastage reduction (S1)	Providing cold storage transportation and warehousing facilities, as well as proper packaging to avoid external shocks that may affect the quality of the products, are all parts of the strategy to reduce food wastage during the logistics portion of the supply chain.
Reducing carbon footprints strategy (S2)	The strategy is to reduce a product's carbon footprint over its life cycle by utilising increasingly eco-friendly packaging, modes of transportation, processing, and storage, thus transitioning to sustainable agro-logistics.
Countering technical failures of equipment (S3)	This strategy makes the technology more sustainable by reducing technical failures, increasing the reliability of machines/equipment and decreasing downtime by increasing the service level.
Developing technologically skilled agricultural manpower (S4)	This strategy aims to promote continuous learning and skill development among farmers and others involved in the agricultural supply chain by providing appropriate training and guidance at the grassroots level by government or government-funded organisations.
Reducing the cost of technology in the agricultural sector (S5)	The strategy is to make technology costs affordable for the agricultural sectors by reducing R&D costs to economically sustainable technology.
Well-connected modes of transportation (S6)	The strategy is to connect one mode of transportation to another, thereby decreasing the supply chain's lead time or delivery time and enhancing the quality of existing supply chain networks, thereby making them more sustainable.
Creating awareness among the farmers about the bright prospect of change (S7)	This strategy aims to educate farmers about the benefits of sustainability and how they can increase their overall productivity by pursuing sustainable goals.
Preparation for cyclic natural disaster (S8)	The strategy is to increase the sustainability of agro-logistics by identifying solutions to various cyclic, natural disasters, such as typhoons, droughts, forest fires, earthquakes and consequential landslides, to minimise disruption to supply chain

Table 4. Pairwise comparison for main category risks

Best to others for 12 respondents												
Experts	Best to Others						TR	SR	RR	IR	ER	
Expert 1	TR						1	5	7	3	9	
Expert 2	TR						1	3	5	9	7	
Expert 3	IR						3	7	9	1	5	
Expert 4	TR						1	7	3	5	9	
Expert 5	TR						1	3	5	7	9	
Expert 6	TR						1	5	3	7	9	
Expert 7	ER						3	7	9	5	1	
Expert 8	TR						1	3	5	9	7	
Expert 9	TR						1	9	7	3	5	
Expert 10	SR						3	1	5	9	7	
Expert 11	RR						5	7	1	3	9	
Expert 12	TR						1	3	9	5	7	
Others to the Worst												
Experts→	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7	Expert 8	Expert 9	Expert 10	Expert 11	Expert 12
Worst Criterion →	ER	IR	RR	ER	ER	ER	RR	IR	SR	IR	ER	RR
TR	9	9	7	9	9	9	7	9	9	7	5	9
SR	5	7	3	3	7	5	3	7	1	9	3	7
RR	3	5	1	7	5	7	1	5	3	5	9	1
IR	7	1	9	5	3	3	5	1	7	1	7	5
ER	1	3	5	1	1	1	9	3	5	3	1	3

Table 5. Criteria weights and ranking of the risks

Main Criteria	Main Criteria Weight	Sub Criteria	Sub Criteria Local Weights	Sub Criteria Global Weights	Ranks
Technological (TR)	0.351	TR1	0.106	0.037	12
		TR2	0.373	0.131	2
		TR3	0.423	0.148	1
		TR4	0.099	0.035	13
Social (SR)	0.187	SR1	0.180	0.034	14
		SR2	0.402	0.075	3
		SR3	0.284	0.053	6
		SR4	0.135	0.025	16
Regulatory (RR)	0.164	RR1	0.229	0.038	11
		RR2	0.185	0.030	15
		RR3	0.456	0.075	4
		RR4	0.131	0.021	18
Individual (IR)	0.169	IR1	0.238	0.040	10
		IR2	0.307	0.052	7
		IR3	0.328	0.055	5
		IR4	0.128	0.022	17
Environmental (ER)	0.129	ER1	0.358	0.046	9
		ER2	0.369	0.047	8
		ER3	0.154	0.020	19
		ER4	0.120	0.015	20

Table 6. Rankings of strategies

Strategies	Main Category Risks		Technological Risks		Social Risks		Regulatory Risks		Individual Risks		Environmental Risks	
	V_i	Rank	V_i	Rank	V_i	Rank	V_i	Rank	V_i	Rank	V_i	Rank
S₁	0.101	7	0.095	7	0.158	2	0.156	1	0.102	6	0.208	1
S₂	0.106	5	0.114	4	0.113	5	0.150	2	0.093	7	0.164	2
S₃	0.117	4	0.132	3	0.116	3	0.099	7	0.089	8	0.097	4
S₄	0.119	3	0.169	2	0.089	8	0.085	8	0.140	4	0.087	6
S₅	0.121	2	0.199	1	0.091	7	0.135	4	0.154	3	0.057	8
S₆	0.103	6	0.101	6	0.205	1	0.113	6	0.162	1	0.099	3
S₇	0.096	8	0.105	5	0.111	6	0.142	3	0.157	2	0.080	7
S₈	0.184	1	0.082	8	0.115	4	0.121	5	0.103	5	0.088	5

APPENDIX A**Table A1**

Best to others for 12 respondents

Experts	Best to Others	TR1	TR2	TR3	TR4
Expert 1	TR3	9	3	1	7
Expert 2	TR3	7	3	1	9
Expert 3	TR2	7	1	3	9
Expert 4	TR2	7	1	3	9
Expert 5	TR2	9	1	3	7
Expert 6	TR3	7	3	1	9
Expert 7	TR3	7	3	1	9
Expert 8	TR3	7	3	1	9
Expert 9	TR3	9	3	1	7
Expert 10	TR3	9	3	1	7
Expert 11	TR2	7	1	3	9
Expert 12	TR3	9	3	1	7

Others to the Worst

Experts→ Worst Criterion →	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7	Expert 8	Expert 9	Expert 10	Expert 11	Expert 12
	TR1	TR4	TR4	TR4	TR1	TR4	TR4	TR4	TR1	TR1	TR4	TR1
TR1	1	3	3	3	1	3	3	3	1	1	3	1
TR2	7	7	9	9	9	7	7	7	7	7	9	7
TR3	9	9	7	7	7	9	9	9	9	9	7	9
TR4	3	1	1	1	3	1	1	1	3	3	1	3

Table A2

Best to others for 12 respondents

Experts	Best to Others	SR1	SR2	SR3	SR4
Expert 1	SR2	9	1	3	7
Expert 2	SR2	7	1	3	9
Expert 3	SR4	7	3	9	1
Expert 4	SR2	7	1	3	9
Expert 5	SR2	3	1	7	9
Expert 6	SR3	7	3	1	9
Expert 7	SR3	9	3	1	7
Expert 8	SR2	3	1	7	9
Expert 9	SR3	3	7	1	9

Expert 10	SR3	9	3	1	7
Expert 11	SR2	7	1	3	9
Expert 12	SR2	3	1	7	9

Others to the Worst

Experts→ Worst Criterion →	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7	Expert 8	Expert 9	Expert 10	Expert 11	Expert 12
	SR1	SR4	SR3	SR4	SR4	SR4	SR1	SR4	SR4	SR1	SR4	SR4
SR1	1	3	3	3	7	3	1	7	7	1	3	7
SR2	9	9	7	9	9	7	7	9	3	7	9	9
SR3	7	7	1	7	3	9	9	3	9	9	7	3
SR4	3	1	9	1	1	1	3	1	1	3	1	1

Table A3

Best to others for 12 respondents

Experts	Best to Others	RR1	RR2	RR3	RR4
Expert 1	RR3	3	7	1	9
Expert 2	RR1	1	7	3	9
Expert 3	RR3	9	3	1	7
Expert 4	RR3	3	9	1	7
Expert 5	RR2	7	1	3	9
Expert 6	RR3	9	7	1	3
Expert 7	RR3	3	7	1	9
Expert 8	RR3	3	9	1	7
Expert 9	RR2	7	1	3	9
Expert 10	RR3	3	7	1	9
Expert 11	RR3	3	9	1	7
Expert 12	RR3	7	3	1	9

Others to the Worst

Experts→ Worst Criterion →	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7	Expert 8	Expert 9	Expert 10	Expert 11	Expert 12
	RR4	RR4	RR1	RR2	RR4	RR1	RR4	RR2	RR4	RR4	RR2	RR4
RR1	7	9	1	7	3	1	7	7	3	7	7	3
RR2	3	3	7	1	9	3	3	1	9	3	1	7
RR3	9	7	9	9	7	9	9	9	7	9	9	9
RR4	1	1	3	3	1	7	1	3	1	1	3	1

Table A4

Best to others for 12 respondents							
Experts	Best to Others			IR1	IR2	IR3	IR4
Expert 1	IR2			3	1	7	9
Expert 2	IR3			7	3	1	9
Expert 3	IR2			3	1	9	7
Expert 4	IR3			9	3	1	7
Expert 5	IR3			3	7	1	9
Expert 6	IR3			3	7	1	9
Expert 7	IR2			9	1	3	7
Expert 8	IR3			7	3	1	9
Expert 9	IR2			3	1	7	9
Expert 10	IR1			1	7	3	9
Expert 11	IR2			7	1	3	9
Expert 12	IR3			3	7	1	9

Others to the Worst												
Experts→ Worst Criterion →	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7	Expert 8	Expert 9	Expert 10	Expert 11	Expert 12
IR4	IR4	IR4	IR3	IR1	IR4	IR4	IR1	IR4	IR4	IR4	IR4	IR4
IR1	7	3	7	1	7	7	1	3	7	9	3	7
IR2	9	7	9	7	3	3	9	7	9	3	9	3
IR3	3	9	1	9	9	9	7	9	3	7	7	9
IR4	1	1	3	3	1	1	3	1	1	1	1	1

Table A5

Best to others for 12 respondents							
Experts	Best to Others			ER1	ER2	ER3	ER4
Expert 1	ER1			1	3	9	7
Expert 2	ER1			1	3	9	7
Expert 3	ER3			9	3	1	7
Expert 4	ER2			3	1	7	9
Expert 5	ER2			3	1	7	9
Expert 6	ER1			1	9	3	7
Expert 7	ER1			1	3	7	9
Expert 8	ER2			3	1	7	9
Expert 9	ER2			3	1	7	9
Expert 10	ER1			1	3	9	7
Expert 11	ER2			3	1	7	9
Expert 12	ER2			3	1	7	9

Others to the Worst												
Experts→ Worst Criterion →	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7	Expert 8	Expert 9	Expert 10	Expert 11	Expert 12
	ER3	ER3	ER1	ER4	ER4	ER2	ER4	ER4	ER4	ER3	ER4	ER4
ER1	9	9	1	7	7	9	9	7	7	9	7	7
ER2	7	7	7	9	9	1	7	9	9	7	9	9
ER3	1	1	9	3	3	7	3	3	3	1	3	3
ER4	3	3	3	1	1	3	1	1	1	3	1	1

Table A6

Rating of Expert 1 for each strategy with respect to all main category risks

	TR	SR	RR	IR	ER
S ₁	1	6	1	4	9
S ₂	1	4	5	4	9
S ₃	9	2	1	3	1
S ₄	9	3	1	1	1
S ₅	9	3	3	6	1
S ₆	4	9	3	3	1
S ₇	3	4	1	9	1
S ₈	4	5	2	3	9