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Unlocking AI's potential in the food supply chain: A novel approach to overcoming barriers

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A R T I C L E I N F O

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A B S T R A C T

This paper delves into the challenges impeding the seamless integration of artificial intelligence (AI) within the food supply chain (FSC) and introduces a novel methodological framework that combines the NK Model with the Decision-Making Trial and Evaluation Laboratory (DEMATEL) technique. Through an exhaustive literature analysis and expert discussions, the research identifies and categorizes significant obstacles to AI deployment in the FSC. These hurdles include the imperative for a skilled labor force, financial limits, regulatory complexity and technological limitations. The unique DEMATEL-NK approach highlights the interconnected nature of these barriers, pinpointing the most critical impediments. The study's implications extend to the broader domains of AI adoption in agriculture and the food industry, offering a nuanced perspective for policymakers, industry stakeholders, and researchers. The findings underscore the imperative of overcoming these barriers for the successful implementation of AI technologies in the FSC, promising advancements in efficiency, quality, and sustainability. The innovative methodology not only sheds light on the interconnectedness of these barriers but also provides a systematic approach for prioritizing and implementing solutions. This research offers a fresh viewpoint on barrier relationships, guiding decision-makers in crafting effective strategies and interventions to propel AI integration in the FSC forward.

1. Introduction

In the era of the digital economy, traditional businesses must digitalize their processes to remain competitive Weill & Woerner [1]. Digital transformation in business relies on the adoption of advanced systems and applications, such as the Internet of Things (IoT), Blockchain Technology (BCT), Cloud Computing, Data Analytics, and Artificial Intelligence (AI) [2]. It also depends on the development and maturation of relevant digital skills and capabilities [3]. Expectations for how AI will harness the information coming in different data points from different technologies are growing, as data becomes more widely available throughout global supply chains [4]. According to a McKinsey study, AI analytics could increase the global GDP by nearly USD 13 trillion (or 16 %) by 2030, with key supply chain-related sectors, (such as logistics and retailing) potentially benefiting the most [5]. The food and beverage industry is projected to reach a market value of USD 29.94 billion by 2026, with a yearly growth rate of 45.8 %. As a result, the deployment of AI in supply chains is expected to significantly enhance efficiency and production over the next decade [6]. Supply chain management is often identified as one of the industries most likely to benefit from new AI technology [7]. However, the full potential of AI in supply chains has not yet been realized, despite the recent in research on the topic [8,9].

By evaluating and categorizing potential stakeholders (such as alternative suppliers), facilities, and technology, the integration of AI into the FSC offers value by (i) Simplifying supply network design and reconfiguration [10]; (ii) Using big data analytics to assess and mitigate risks, thus enhancing supply chain resilience [11]; (iii)Enabling near

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real-time, automated, and optimal decision-making by analyzing vast amounts of data from various sources (such as the web, social media, and information systems of supply chain actors) [12]; (iv) Enhancing information validation for specific purposes like contracting, while enabling learning, reasoning, and self-correction of supply chain activities [13]. Given the increasing need for transparent traceability and product safety assurances, the application of data-driven digital technologies is particularly beneficial in the context of the FSC. Emerging technologies such as AI can play a crucial role in creating synchronized supply networks that thrive by sharing knowledge and resources collaboratively, addressing the complex and uncertain interactions that characterize supply chains [14]. Studying AI in the context of the food supply chain is essential due to its ability to enhance efficiency, reduce waste, and ensure food safety. AI-driven insights improve demand forecasting and inventory management, leading to cost savings and sustainability. Moreover, AI enhances traceability and transparency, crucial for maintaining food quality and safety standards as compared to other emerging technologies.

While the studies mentioned above emphasize the importance of AI in supply chains, they often fall short in providing managers with context-specific insights that they can readily apply when considering AI integration within their organizations. Therefore, the objective of this paper is to deepen our understanding of this topic within the context of the FSC, which is in urgent need of AI intervention. This need arises due to specific challenges, such as product perishability and waste, which AI technology can effectively address in the FSC. The FSC encompasses various systems involving people, organizations, activities, information, and resources related to food production, processing, distribution, and disposal, to deliver goods from farmers to consumers [15]. Unlike other supply chains, the FSC requires quality adjustments at every stage until the product reaches consumers, making the preservation of food safety and quality throughout the FSC a complex challenge [16]. It is argued that AI can enhance FSC efficiency by facilitating greater supply chain integration [17]. A 2017 Gartner survey revealed that only 6 % of businesses had deployed AI, while nearly 59 % were still in the information-gathering stage to determine its potential impact on their corporate strategies [18]. Wu et al. [19] noted that much of the research on the adoption of cutting-edge technology, such as AI, has been conducted in developed nations.

The adoption of AI is expected to address issues related to food quality and safety, improve transparency, and traceability, and enhance the efficiency of FSCs [20–22]. However, due to the diverse nature of FSC, it is essential to identify the barrier that can facilitate AI adoption and simplify the process. By identifying these factors, it becomes possible to create suitable methods for implementing AI in FSCs. This study employs several significant variables from the "Technology, Organization, Environment" (TOE) framework to construct a conceptual framework illustrating the application of AI within the FSC in developing countries, a rapidly growing market. There is a lack of a thorough synthesis of all studies and approaches, and a broad range of methodologies are used in the subject [23]; used a simulation model to enhance the performance of the food reclamation center, empirical approaches to address the results of food insecurity [24], and a thorough evaluation to investigate supply chain interruptions. Developing countries like India face unique challenges in their food supply chains, such as infrastructure limitations and higher rates of food loss. Studying AI's potential in these contexts provides targeted solutions that can significantly enhance efficiency, reduce waste, and improve food security.

The authors aim to address the following research questions (RQs) to investigate and fill the gaps in the literature:

RQ1: What are the barriers to AI adoption in the FSC in developing countries, and how do they interrelate?

RQ2: What is the most effective sequential implementation strategy for FSC in developing countries to achieve AI adoption?

This research has several implications that contribute to the existing body of literature. First, it introduces AI adoption in the FSC as a mediator between sustainability and SME success, expanding the available research on this topic. Second, the study identifies AI adoption barriers in the FSC through a thorough literature analysis, subsequently validated by experts. Third, it creates a framework for AI adoption in the FSC by merging the DEMATEL technique with an NK model to assess linkages at various analysis levels. Fourth, the methodology is applied using empirical data from a single FSC company. Fifth, this study provides significant theoretical and managerial insights for managers, policymakers, and business practitioners dealing with the previously mentioned challenges. Finally, to further enrich the body of literature, the study suggests future research directions for AI adoption in the FSC. Table 1 presents the various barriers categorized under the headings of Technology (T), Environment (EN), and Socio-economic (SE). The authors identified 15 barriers to AI Adoption in the FSC by meticulously reviewing prior research and conducting a systematic literature study.

The remainder of the paper is structured as follows: Section 2 presents the literature review, focusing on AI adoption in the FSC, barrier identification, and detailed explanations of these barriers. Section 3 covers the methodology and includes an explanation of the data collection and analysis procedures. Section 4 introduces the application and provides background information on the case. Section 5 analyzes the results and presents the discussion. Finally, Section 6 covers the conclusion, future research directions, and study constraints.

2. Literature review

The lack of transparency and traceability in the FSC has been underscored by various food crises worldwide [38]. Given the unpredictability and cyclical demand for food products, monitoring product reliability in an FSC is crucial [38]. Food security, safety, and management are key concerns for all countries. In developing markets like India, post-harvest losses account for over 40 % of all food losses, with storage loss being a primary cause [39]. The inadequate FSC is a major factor contributing to these losses, marked by issues such as insufficient storage facilities and poor coordination between supply chain channel partners [40].

Food products possess unique qualities such as perishability, seasonality, and temperature sensitivity, making the FSC an appealing setting for research [41]. Consequently, the FSC faces challenges related to product perishability and waste, among other aspects of the supply chain [42].

In recent years, there has been considerable attention on the potential of AI to revolutionize the FSC. The importance of a flexible, efficient, and sustainable FSC has grown as the global population continues to expand, and consumer demands become more complex [43]. Many studies emphasize the advantages that AI can bring to the FSC, such as predictive analytics, machine learning, and data mining, which can enhance distribution, demand forecasting, inventory management, and quality control procedures [44,45]. AI can also improve transparency and traceability, contributing to increased food safety and reduced fraud.

The adoption and usage of AI are examined using the Technology-Organization-Environment (TOE) and Human-Organization-Technology (HOT) frameworks, which consider organizational, human, technological, and environmental variables as CSFs [46]. These frameworks encompass both internal and external technologies, procedures, and tools demonstrating innovative qualities or elements in the technology adoption study [27].

The adoption of AI in the FSC is influenced by various socio-economic factors, including committed resources, organizational culture, and other organizational traits [47]. Strong managerial support is crucial for successful AI deployment in the FSC, as it enables businesses to navigate the complexities of cutting-edge technologies and increases the adoption rate [48]. Environmental factors are linked to the

Table 1
Barriers to AI adoption in the FSC.

Sr. No.	Barrier	Description	Citation
Technology	Lack of Technology readiness	This challenge encompasses inadequate digital infrastructure, limited access to AI resources, and a shortage of skilled personnel to effectively deploy and manage AI technologies, impeding their successful integration within the supply chain.	[25]
	Unclear about relative advancement/ perceived benefit	This lack of clarity can hinder decision-makers from recognizing the significant improvements in efficiency, cost savings, and overall performance that AI technologies can offer, thereby delaying their adoption and implementation. Clarifying the tangible advantages of AI is crucial for fostering its acceptance and integration in the FSC.	[26]
	Lack of Compatible facilities for testing and trial ability of AI Technology	This limitation hinders stakeholders from effectively evaluating AI's performance, scalability, and compatibility within their specific supply chain processes, thus acting as a barrier to its adoption. Establishing appropriate testing facilities is essential for building confidence in AI systems and facilitating their successful integration into the FSC.	[27]
	Lack of sufficient privacy and security	This denotes the inadequate measures to protect sensitive data and ensure the security of AI applications. This challenge raises concerns about data breaches, regulatory compliance, and consumer trust, impeding the widespread adoption of AI technologies in a sector where data privacy and security are paramount.	[28]
Organization	Lack of clear linkage between vision and strategy	This issue results in a disconnect between the overarching goals and the actionable strategies needed for successful AI implementation, leading to inefficiencies and challenges in aligning technological advances with the broader objectives of the supply chain. Clarifying the vision-to-strategy pathway is essential for effectively leveraging AI in this critical domain.	[29]
	Lack of top management support and ownership	This challenge can hinder the allocation of resources, decision-making, and overall momentum required for successful AI integration, potentially causing delays and impediments in realizing the technology's potential benefits. Strong top management support is crucial for driving the AI agenda and ensuring its successful implementation within the supply chain.	[30]
	Lack of Behavioral change management initiatives for AI adoption	It refers to the oversight of programs aimed at facilitating the necessary behavioral changes in employees and stakeholders. This issue can result in resistance to adopting AI technologies due to unfamiliarity or fear of change, obstructing the seamless integration of AI solutions into the supply chain	[31]
	Lack Establish sufficient. resources and competencies for AI Adoption	It highlights the inadequacy of both financial and human resources as well as the necessary skills to effectively implement AI solutions. This challenge can hinder the development, deployment, and maintenance of AI systems, slowing down their adoption within the supply chain.	[32]
	Lack of Organization culture and environment for information sharing	This challenge can stifle the dissemination of knowledge and data crucial for effective AI implementation, inhibiting the development of innovative solutions and efficient decision-making.	[33]
	Proper training for staff and end-users	The absence of such initiatives can result in insufficient knowledge and competence among employees and end-users, leading to suboptimal AI utilization. Providing adequate training is crucial for enabling individuals to effectively engage with AI technologies, thereby enhancing their adoption and the overall performance of the supply chain.	[34]
Environment	Lack of Ethics in data collection	This issue can lead to concerns about privacy violations, data misuse, and ethical dilemmas when employing AI technologies. Adhering to strict ethical principles in data collection is imperative to maintain trust and integrity in AI applications, especially in a sector where consumer data and food safety are paramount.	[29]
	Lack of Regulatory and compliance requirements	This challenge can create uncertainty and reluctance to adopt AI technologies, particularly in a sector where safety and quality standards are paramount. Establishing comprehensive regulatory frameworks and compliance requirements is vital for ensuring the	[32]

(continued on next page)

Table 1 (*continued*)

Sr. No.	Barrier	Description	Citation
		responsible and secure implementation of AI in the FSC, addressing safety and quality concerns, and fostering trust among stakeholders.	
	Peer/competitor pressure	This factor can lead to a rush to embrace AI without proper planning or understanding, potentially resulting in suboptimal implementation. While peer pressure can stimulate AI adoption, it's crucial to balance it with a strategic and well-informed approach to ensure that AI technologies are integrated effectively and align with the specific needs and objectives of the FSC.	[35]
	Demand volatility	This dynamic challenge can hinder the effective implementation of AI, as it may lead to issues such as overproduction or underproduction. Successfully addressing demand volatility requires AI systems to adapt and respond swiftly to changes in demand patterns, making it a critical focus for supply chain efficiency and AI integration efforts in the developing countries food industry.	[36]
	Lack of Institutional based trust	This lack of trust can hinder the acceptance and widespread adoption of AI technologies, as stakeholders may be hesitant to rely on these institutions for data handling, decision-making, and the overall management of AI systems.	[37]

organization's external environmental aspects [49]. Institutional trust plays a significant role in shaping an organization's perspective on the safety of implementing AI in the FSC [50]. The formation of an AI implementation team is vital for the adoption and effective use of AI in the FSC to ensure that AI's benefits are maximized.

Although there have been numerous studies on the practical adoption of disruptive technology models in various industries [46], research on the function of CSFs in the AI adoption process in the FSC is scarce [51,52]. This is despite the growing number of studies in the field of disruptive technologies such as Blockchain Technology (BT), Cloud Computing (CC), Internet of Things (IoT), Big Data Analytics (BDA), Drones, and others. AI has the potential to revolutionize FSCs, but due to the complexity and disorganization of developing country FSCs, along with the involvement of numerous intermediaries [53], there is a need for a suitable integration platform, where technologies like AI can play a vital role. The study is the first of its kind to identify Barrier using the extended TOE frameworks and to analyze them using the DEMATEL-NK Model. It provides valuable insights for academics and practitioners on how to effectively implement AI technology to enhance organizational supply chain performance. The list of 21 barriers including technological, environmental, and socio-economic factors, is comprehensive enough to encompass barriers that influence AI adoption in the FSC, particularly in developing economies. The study's purpose is to understand how barriers impact AI adoption and its sequential implementation. The existence of this knowledge gap has driven researchers to focus on FSCs, providing insights that can guide experts and managers on efficient AI deployment, helping allocate resources where necessary, and ensuring successful AI implementation.

3. Methodology

This section provides additional details on the foundational concepts and history of DEMATEL, as well as the NK Fitness Landscape model (NK Model). Next, the DEMATEL technique is introduced, which can be employed to assess the interdependencies among AI adoption barriers in the FSC and understand their impact on performance. The NK fitness landscapes model (NK model), which aids in creating a path framework (implementation sequence) for specific strategies, is then explained. Ultimately, this study integrates these two approaches to offer an FSC company a path framework and proposes a novel method for evaluating AI adoption. The research methodology framework is illustrated in Fig. 1. A Total of nine experts were chosen for the study with criteria of a minimum of 10 years of experience and their AI implementation and different stages such as strategic, tactical, operational, and inter-organizational. A description of the experts is given below in Table 2.

DEMATEL is chosen over AHP (Analytic Hierarchy Process), TISM (Total Interpretive Structural Modelling), ISM (Interpretive Structural Modelling), or any other MCDM technique since it splits challenges into cause-and-effect groups, as well as indicates the intensity of their effects [54]. Other methods, like the AHP technique, are not able to map the interdependence and the cause–effect relationship between the factors [55]. Through matrices or diagraphs, policymakers can obtain observations with a measurable and visual kinship among difficulties [56]. It features a large response range of (0, 1, 2, 3, and 4) to investigate the cause-and-effect relationship between the challenges. The identification of issues also aids managers in developing efficient strategies for dealing with them [54]. used the DEMATEL to evaluate the adoption of ICTs in Indian food SMEs. DEMATEL was used by [57] to examine the interconnections between barriers to sustainable production [58]. analyses cause and effect groups of e-waste mitigation measures using the DEMATEL approach. DEMATEL visualizes how different barriers to AI integration in the food supply chain (FSC) are interconnected, highlighting which barriers influence others directly or indirectly. Through relation analysis, we identify which barriers act as drivers or inhibitors within the system, thereby elucidating causal pathways that affect the successful adoption of AI technologies. It quantitatively assesses the strength and direction of relationships, providing insights into which barriers are most critical and require prioritized interventions.

3.1. DEMATEL method

The DEMATEL technique was developed by the Battelle Memorial Institute's Geneva Research Centre and has been applied to analyze and resolve a variety of complex and interrelated problems [59]. DEMATEL is a technique for analyzing and visualizing a structural model of intricate causal relationships. It has found applications in various fields, including supplier selection, hospitality, business process management, and green supply chain management. In this study, we build upon the version introduced by Fontela and Gabus [60] and provide the following steps for utilizing DEMATEL.

(1) Generating the direct-relation matrix.
(2) Normalizing the matrix.
(3) Creating the total-relation matrix.
(4) Constructing a causal/effect diagram.

3.2. NK fitness landscape model

The NK model [61] is a fundamental yet powerful analytical

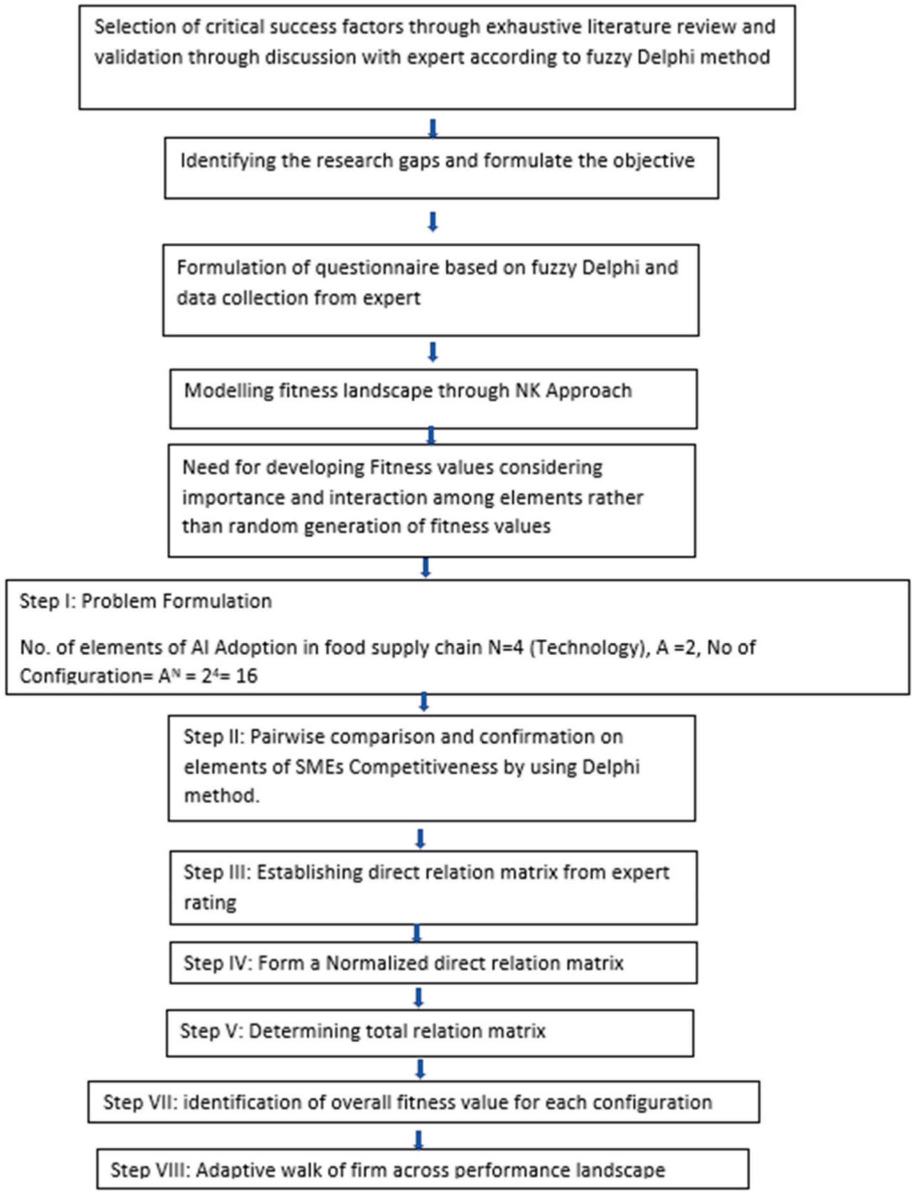

Fig. 1. Methodology framework.

framework for studying solutions to organizational problems through adaptive searches. While originally developed to model the evolution of biological systems toward greater fitness, it has gained more widespread acceptance in the organizational research literature Dosi et al., [62]. However, it remains relatively less known in the supply chain management literature, particularly in the context of environmental or green supply chain management [63]. Nevertheless, this method has been employed in various other studies, such as optimizing paths for low-carbon supply chain practices implementation [64], sustainable competitiveness practices for SMEs by Ghag et al. [65] and finding optimal paths for overcoming barriers in green construction supply chain management [66], interdependence and network level trust in supply chain network (Capaldo and Giannoccaro, 2015), assessing the influence of organization in supply chain management.

The NK Model comprises two key components. The first stage involves finding a randomly generated fitness landscape, where higher peaks represent optimal component combinations and solutions. The second aspect involves agents searching for specific terrain to enhance their "fitness" or performance. The system uses search algorithms to navigate the fitness landscape and identify optimal areas, representing the best long-term optimum solutions. These search techniques, consisting of routines and heuristics, enable the system to modify and rearrange the values of the N components. The system transitions to the new configuration, which represents a position on the landscape, when the new system fitness value exceeds the current system fitness value. The NK model selects the most effective path through the landscape from various options to enhance the performance of supply chain relationships. The degree of interaction between components, denoted as K, influences the landscape's geometry.

If K has a value of zero, the components are independent of each other, and their interdependencies increase as K increases. The higher the value of K, the outcome will be along the terrain and closer to the nearby mountain. K serves as a measure of system complexity because as K increases, the web of dependencies also grows, resulting in a rougher landscape [67].

3.3. Case background and application

The sequential strategies for overcoming barriers to AI adoption by FSC firms may vary from one firm to another and require in-depth

Table 2
Expert quotes and profile.

Company	Implementing AI	Designation	Experience in years	Quotes
ABC	Strategic Level	Senior Manager	12	Agility, vision, and the capacity to quickly adjust to shifting market conditions are necessary for navigating demand volatility.
EFG	Tactical level	Director	14	Support from top management is more than just a checkmark; it's the essential component that turns aspirational ideas into attainable goals.
HTR	Strategic Level	Owner	25	Having the newest tools alone won't make you technologically ready; you also need to have the organizational attitude, infrastructure, and skills necessary to use them to their full potential.
JKL	Strategic Level	Director	20	A distinct vision acts as a roadmap for companies travelling towards AI-enabled supply chains, directing them through challenges and unknowns.
MHT	Operational Level	Operation Head	12	"The implementation of AI in the food supply chain is hampered by regulatory complexity and unpredictability. Food laws differ from place to place and are frequently updated and modified".
FRY	Intra Organizational Level	Supply chain Manager	15	A significant obstacle to the application of AI in the food supply chain is the lack of access to high-quality data. Even though a huge amount of data is produced at different points in the supply chain, a large portion of information is incomplete, unstructured, or of low quality.
UEW	Operational Level	Operations Head	16	In the age of data-driven decision-making, maintaining security and privacy isn't just required by law; it's also morally necessary to preserve customer confidence and brand reputation.
YTH	Intra Organizational Level	Deputy Manager	18	Though AI has enormous potential benefits for the food supply chain, organizations run the risk of losing out on opportunities and resources if it's unclear how these benefits will materialize.
MVB	Operational Level	Senior Manager	15	The availability of resources is the cornerstone on which innovation in the food supply chain is built. Ample resources support the development and evolution of AI-driven solutions, similar to how fertile soil supports a crop, guaranteeing a plentiful crop of effectiveness, sustainability, and resilience.

examination rather than simply applying a generic approach. While generalized models are beneficial for many organizations as they provide a comprehensive understanding of problems and potential solutions, they are more effective when an underlying theory has been debated and discussed over time in various contexts. Given that the topic of AI adoption in FSC is still in its infancy and lacks literature describing causal linkages between explanatory variables, a case study technique would be more applicable in this situation. According to Yin [68], case study analysis is appropriate when there is theoretical uncertainty. Case studies are epistemologically justified under theoretically confusing conditions or when facing problems that demand inquiry rather than validation. AI adoption in FSC is a phenomenon that defies theoretical explanation and requires a careful examination of businesses implementing it. The case study technique is suitable for these firms, where the main objective is not to statistically generalize outcomes for the entire population but rather to explore in detail the sequential overcoming of barriers to AI adoption in FSC and focus on creating links between them. To create and evaluate the theory, various data sources, including archives, interviews, questionnaires, and diverse observations, were combined using the case study approach [69]. The study's sample size is modest because AI in FSC is not well-researched or understood in developing countries. Case A, a firm focused on AI adoption in FSC, was selected for our case study. Several studies argue that individual biases may be a concern in such investigations, and a single respondent case study does not provide an authentic or thorough image of the organization under consideration [70]. The data were collected from the manager and owner of the firm, both actively involved in strategy formulation and possessing extensive expertise in FSC and AI.

3.4. Methodology steps

A combined DEMATEL and NK approach is presented to establish a framework for AI adoption in the FSC process, utilizing data from the case study. A relative connection model for relationship behaviors and AI adoption efforts is developed using DEMATEL. The NK method is employed to construct the process framework for strategies and relational practices. The following outlines the main steps in the DEMATEL and NK approach, with case organization data used in examples to illustrate the steps.

Step 1: Design the Barrier to AI Adoption Structure

This is the initial step where the generic NK model data structure is introduced. This structure is essential for determining relevant information and specifications. K will represent the degree of dependence between the barriers to AI Adoption. N = 4 barriers include Lack of Technology readiness, Unclear about relative advancement/perceived benefit, Lack of Compatible facilities for testing and trial ability of AI Technology, and Lack of sufficient privacy and Security. The interdependencies between the barriers can be identified using DEMATEL.

Step 2: Direct relation matrix

Experts were asked to compare two things in pairs using a 5-point linguistic scale. Table 3 below outlines the number of linguistic scales. The triple bottom line corresponds to four full matrices. Generally speaking, Matrix M is the starting matrix.

$$M^e = C2\begin{vmatrix} 0 & m_{12} & m_{1n} \\ m_{21} & 0 & m_{2n} \\ m_{n1} & m_{n2} & 0 \end{vmatrix}$$

The evaluators of each organization first establish the pairwise impact linkages M between barriers of AI adoption. Every diagonal member in the matrix will be zero and will have no bearing on one another.

Step 3: Aggregate direct relation matrix

The following equation yields the aggregate relation matrix:

$$M = \left(\sum_{i=1}^{E} M^e\right) | \, E$$

The direct relation matrix of the organization's factors will be integrated into an aggregate relational matrix, totaling 3 aggregate matrices The direct relation matrices for the three categories are shown in Appendix A1, A4, and A7.

Step 4: Normalize aggregate direct relation matrices.

The normalized matrix can be obtained from the below equation

$$s = \frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{n} mij}, i,j = 1,2,\ldots,n$$

$$N = s \times M$$

Table 3
DEMATEL linguistic measures.

Linguistic terms	Number
No influence	0
Very low influence	1
Low influence	2
High influence	3
Very high influence	4

The direct relation matrix for the case will be correspondingly normalized to N. Tables A2, A5, A8, in Appendix Table provide the normalized matrix.

Step 5: Total Relation matrix

The expression below can be used to find the complete relation matrix T.

$$T = N + N^2 + N^3 + \ldots = \sum_{i=1}^{\infty} N^i = N(I - N)^{-1}$$

The normalized matrix will be used to calculate the total relation matrix. Appendices A3, A6, and A9 display total relation matrices.

Step 6: Developing causal influence of the factors

Sub Step 1: From the whole relation matrix, find the values of R and D, or the sum of the row and column for each row i and each column j.

R = $\sum_{i=1}^{n} tij$;

D = $\sum_{j=1}^{n} tij$;

The values of Ri indicate the whole of factor I's influence over the other sustainable competitiveness factor. Similarly, column value Dj indicates the total of the influences, both direct and indirect, that decision variable j has on other decision variables.

The matrix T and additional submatrices of subfactors are used to create the total relation matrix. The table below displays R and D's values.

Step 2 Sub: Utilizing the following formula, find the overall prominent factor and net effect factor.

$$P = \{R_i + D_j | i = j\}$$

$$E = \{R_i - D_j | i = j\}$$

The net cause and effect index is represented by the value P. The relationship with the factor is stronger the higher the P value. Additionally, Value E illustrates the overall net cause and effect of Factor I.

The following stage involves simulating the barriers using the NK Model to extract the optimal performance for the specified interdependencies from the total relationship matrix.

Step 7: Developing the NK Model for AI adoption in FSC.

To find the essence of the AI in FSC in the parsimonious form we have used the Technology, Organization, and Environment (TOE) framework. An NK Model consisting of N = 4 barriers from technology and 6 and 5 barriers from socio-economic and environment, respectively, is developed and overcome sequentially. Each strategy has two solutions: first, to apply, and second, to not apply.

Four strategies of system configuration can be represented by the strategic NK Model using this method. There will be 16 different configurations for the outcome. Every strategy may have a different set of obstacles.

Step 8: Identify the overall fitness value for each strategy.

The NK model has three sub steps.

Sub Step 1: Calculate the fitness value of each strategy.

Fitness values, or performance if the strategy were used independently, can be ascribed to each barrier. The entire relation matrix can be used to obtain the fitness value.

$$f_i = t_{in}$$

where t_{in} is the relation between the barrier in the total relation matrix.

Sub Step 2: Calculation the interdependencies among the practices.

Interdependencies within a system are identified by a localized pattern of interaction. In this case, the entire relation matrix ignores the row and column. The following equation yields the result as a structured interdependency matrix.

$$I_{ij} = t_{ij} \; for \; i \; and \; j = \{1, \ldots, n-1\}$$

Where K = 2, according to the interdependency matrix I_{ij}, which represents each practice. In calculating its fitness value, each barrier is dependent on K other barrier.

Sub Step 3: Calculating overall Fitness value for each configuration.

Finding the overall fitness value point for each of the possible landscape configurations is the current objective. The two equations below are used to compute total fitness, which is the sum of the values assigned to each strategy's fitness value and interdependency.

$$\mathrm{F} = \sum_{i=1}^{N} di \;\; for \;\; ci = 1$$

$$d_i = f_i + \sum_{j \in \{j | c_j = 1, |j| \leq K\}} f_j * I_{ji} \; i \neq j$$

Step 9: Find the optimal process for Sustainable Competitiveness of SMEs

The best sequential procedure for the company and its supply chain to overcome barriers will be identified in this step. After the performance landscape is generated, the organization explores it in search of implementation combinations that yield superior results. While it is not feasible to create an exact 3D depiction of the "landscape," we blend genomic values around the x-axis, barriers along the y-axis, and performance or fitness value along the z-axis. We selected these combinations because they are easy to graph in three dimensions, but we might have chosen other combinations to aid in the building of the 3D diagram path that comprises the performance landscape. The adapted walk is the name of the search route. The fundamental idea of the adaptive walk in this research and methodology is for an organization to make little, one-at-a-time changes as they search for better solutions. The optimal route ultimately results in a combination when all technology barriers are used (1, 1, 1, 1). An organization's progression from position 0 to position 1, then to position 2, and ultimately to position 4, where it reaches its zenith, is schematically illustrated in Fig. 2. Starting at (0, 0, 0, 0), the organization has a performance value of 0. This is the organization's best option for overcoming the barriers. Details as shown in Figs. 2-6, and the fitness values for Socio-economic and environment are shown in Appendix Table No. A10 and A11. The term "implementation combinations" refers to the various pathways or strategies derived from the NK model that guide the sequential implementation of solutions to overcome barriers in integrating AI within the food supply chain (FSC). While the optimal process mentioned in our study does relate to identifying the most effective strategies, it is distinct from implementation combinations. The optimal process signifies the most efficient route or set of actions derived from the NK model's fitness calculations and

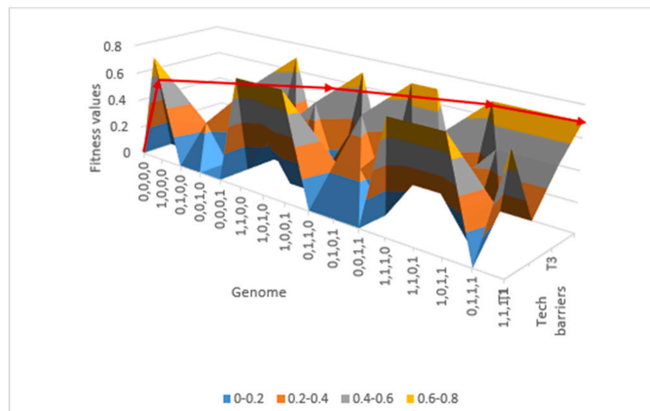

Fig. 3. Landscape of technology barriers.

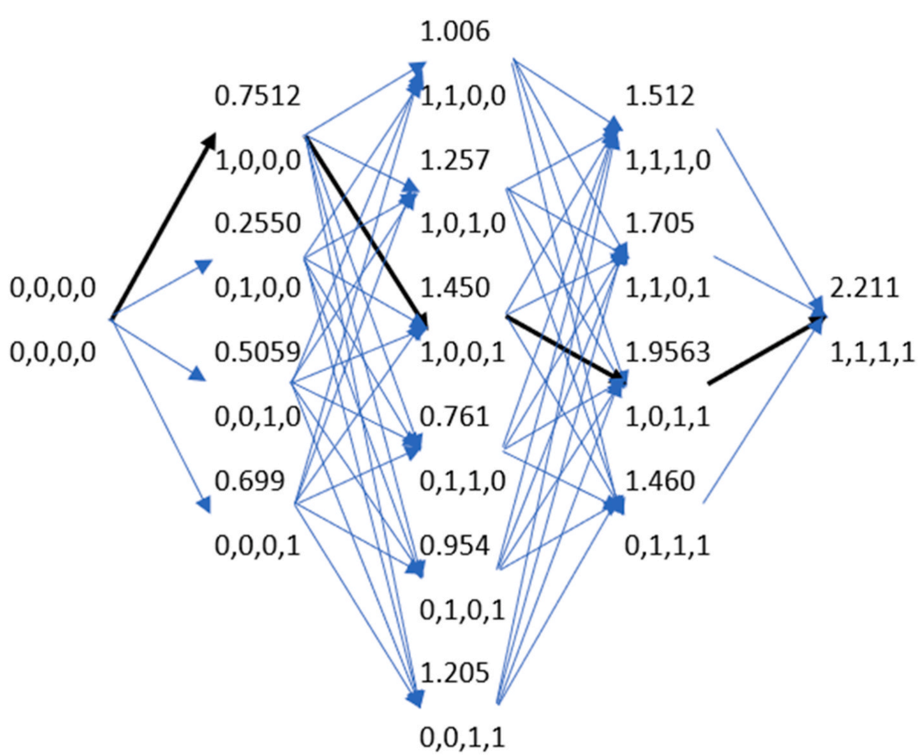

Fig. 2. Fitness values with each combination.

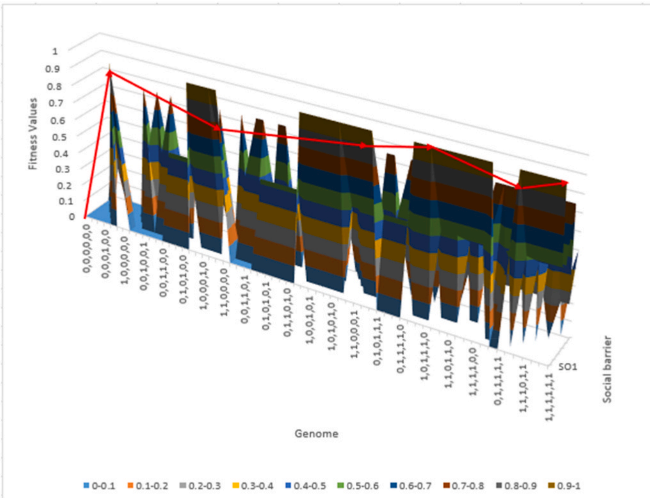

Fig. 4. Landscape of socio-economic barriers.

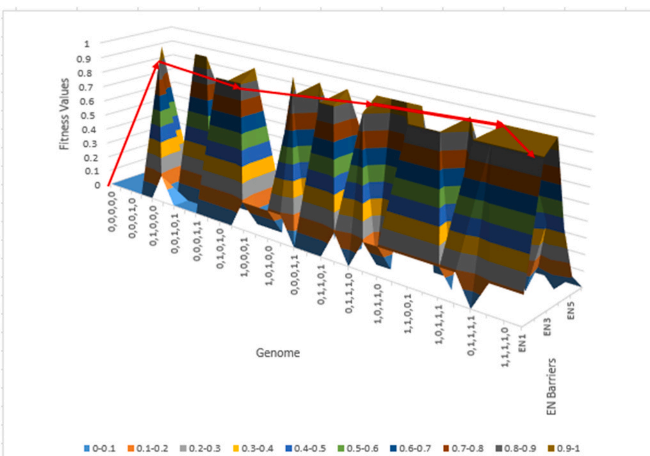

Fig. 5. Landscape of environmental barriers.

evaluations using the DEMATEL technique. It serves as a strategic framework for decision-makers to prioritize and execute interventions systematically. In contrast, implementation combinations encompass a broader scope, encompassing multiple possible pathways and interventions tailored to address specific barriers identified in the FSC. Together, these elements contribute to a comprehensive approach for stakeholders to navigate and surmount obstacles hindering AI adoption in the FSC effectively.

4. Result and discussion

Through the use of the DEMATEL and NK models to analyze the quantitative survey results, the general path model for overcoming barriers (Fig. 2) in AI implementation in FSC was created. According to the path results, the case study organization should first address technology readiness and its impediments to successful integration within the supply chain. Respondents emphasize that overcoming this significant technology barrier is a crucial first step, laying the groundwork for effective AI adoption. Technology readiness depends on factors such as well-established infrastructure and the availability of trained human resources [34]. The next important technology barrier that needs to be overcome is the Lack of sufficient privacy and security. The adoption of AI in FSCs is facilitated by competitive pressure, as increased competition among firms leads to a higher uptake of technology. However, ethical concerns about data collection draw attention to privacy issues raised by gathering users' personal information [29], which could impact FSCs' acceptance and usage of AI technologies [29]. The remaining technology barriers can be addressed in the order of overcoming the Lack of Compatible facilities for testing and trial ability of AI Technology first and then achieving clarity about relative advancement/perceived benefit. There aren't many variances in fitness levels when it comes to switching the sequence of these two technology barriers. Organizations are free to choose the precise overcoming sequence based on their unique circumstances.

In the case of Socio-Economic barriers, the first significant barrier that needs to be overcome is the lack of clear linkage between vision and strategy. According to Saberi et al. [30], supply chain companies should incorporate AI and information technologies throughout the supply chain network to preserve the organization's alignment between its vision and mission. This will help ensure that the supply chain is resilient and efficient. The next barrier in the overcoming order of the socio-economic category is a lack of top management support and ownership. According to a study by Yang et al. [71], top management commitment and support have a significant association with technology adoption. These relationships are necessary for formulating plans and guiding the adoption of the latest emerging technologies. Next, the order of socio-economic barriers includes a Lack Establish sufficient resources and competencies for AI adoption, Proper training for staff and end-users, a Lack of Behavioral change management initiatives for AI adoption, and lastly, is Lack of Organizational culture and environment for information sharing.

Along with Technology and socio-economic barriers, the organization should also overcome environmental barriers, which are an equally important measurement category. In the Environment category, the first important barrier that needs to be overcome is Peer/competitor pressure. To achieve the goal of an agile and resilient FSC channel, the developing countries' FSC industry can benefit greatly from peer and competitive pressure, encouraging the use of cutting-edge technologies like IoT, AI, machine learning (ML), and blockchain technology [72]. The next sequential barrier after peer pressure is the lack of regulatory and compliance requirements. In general, federal agencies' regulatory compliance frameworks are beyond the control and limited access for FSC firms. Therefore, the use of AI technologies in the supply chain can be supported by the presence of appropriate rules and adequate financial investment [32]. The next sequential important barrier is Demand Volatility in the environment category. Due to erratic swings in demand, businesses must use cutting-edge technologies to exhibit a high degree of agility to minimize the unpredictability and volatility of the market demand for the food supply [37]. The last two sequential but equally important barriers are the Lack of institutional-based trust and the Lack of Ethics in data collection.

The study integrates Figs. 3-5 to construct a general path framework for overcoming barriers to AI adoption in FSC. The NK model, influenced by interdependencies from the DEMATEL technique, generates the performance landscape for combinations of various technology, socio-economic, and environmental barriers. The fitness values of each barrier are shown in Table 4, A10 and A11.

4.1. Theoretical contribution

This study represents an early effort to help to overcome barriers to AI adoption in FSC by demonstrating how an organization's integration of AI technologies helps it achieve sustainable FSC, which can result in firm competitive advantages. The study proposes a TOE theoretical viewpoint to validate the barriers to AI adoption in FSCs. Owing to the highly competitive landscape and fierce competition among supply chain companies over customer satisfaction and legally mandated requirements, the TOE framework must be included to overcome the barrier of AI adoption in the FSC. Our research model, which was based on the framework proposed by [73], examined the challenges' adoption

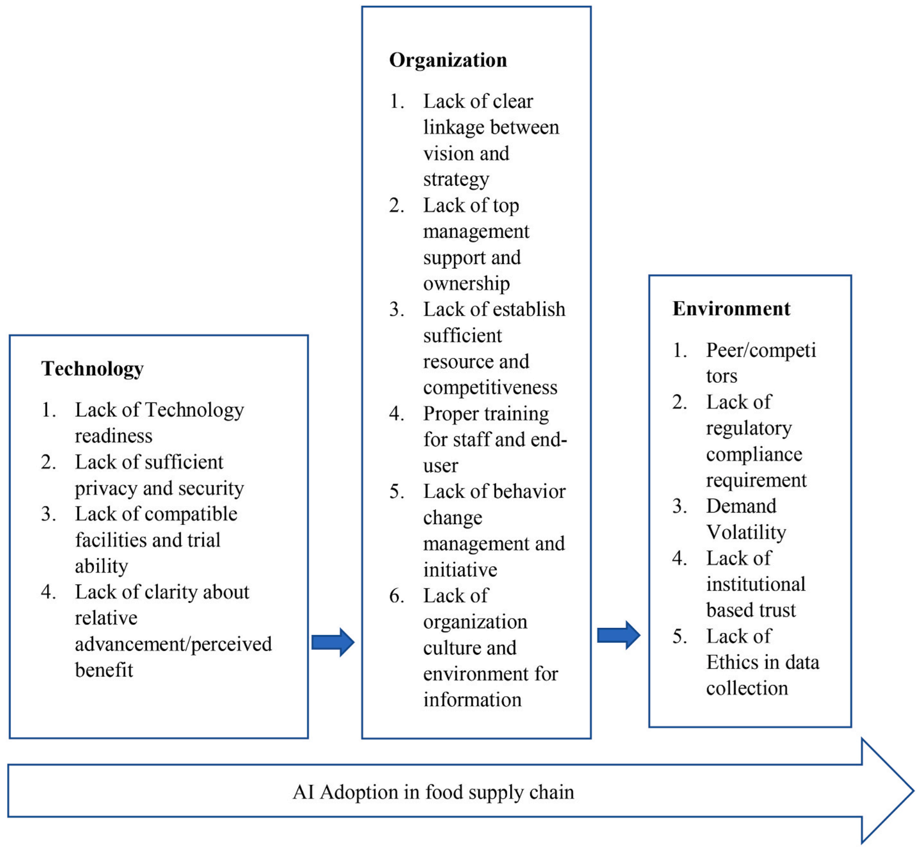

Fig. 6. The best optimal path framework for overcoming AI Barriers in FSC.

Table 4
Fitness values for technology barriers.

Genome				T1	T2	T3	T4	Fitness	Rank	Path
0	0	0	0	0	0	0	0	0		
1	0	0	0	0.751267	0	0	0	0.751267	1	T1
0	1	0	0	0	0.255095	0	0	0.255095		
0	0	1	0	0	0	0.505957	0	0.505957		
0	0	0	1	0	0	0	0.699077	0.699077		
1	1	0	0	0.751267	0.255095	0	0	1.006362		
1	0	1	0	0.751267	0	0.505957	0	1.257224		
1	0	0	1	0.751267	0	0	0.699077	1.450344	2	T4
0	1	1	0	0	0.255095	0.505957	0	0.761052		
0	1	0	1	0	0.255095	0	0.699077	0.954172		
0	0	1	1	0	0	0.505957	0.699077	1.205034		
1	1	1	0	0.751267	0.255095	0.505957	0	1.512319		
1	1	0	1	0.751267	0.255095	0	0.699077	1.705439		
1	0	1	1	0.751267	0	0.505957	0.699077	1.956301	3	T3
0	1	1	1	0	0.255095	0.505957	0.699077	1.460129		
1	1	1	1	0.751267	0.255095	0.505957	0.699077	2.211396	4	T2

of AI. This was accomplished by integrating the most important constructs for each of the three TOE framework aspects that have been researched in the literature. Lastly, by understanding the contextual diversity of technology adoption models, a theoretical lens on the TOE framework and the study's results in an emerging economy setting is anticipated to enhance and add to the constantly expanding literature on AI-SCM.

The three dimensions—technology, organization, and environment—that were put forth are important for SMEs' adoption. The majority of the barriers we learned from our research are specific to AI adoption, but it is important to keep in mind that some barriers such as lack of technological readiness, lack of adequate security and privacy, competitive pressure, regulatory and compliance requirements, and perceived benefit are recognized as conventional and can be found in other technological development receptions. Lastly, this work is an initial attempt to employ a unique NK- DEMATEL- Fuzzy Delphi method to sequential overcome the barriers and simplify the adoption of AI in the developing country FSC environment. It is a methodological application.

This study contributes theoretically by exploring the under-researched application of AI in the food supply chains of developing countries, particularly India. It extends existing literature by integrating AI with supply chain management theories, highlighting how AI technologies can address specific challenges like infrastructure deficiencies, inefficiencies, and food wastage prevalent in these regions. The study introduces a novel framework that links AI capabilities with supply chain performance metrics, providing a comprehensive understanding of how technological advancements can bridge gaps in developing economies. By doing so, it offers a new perspective on the role of AI in enhancing food security and operational efficiency in contexts with distinct socio-economic dynamics.

4.2. Practical implications

For supply chain managers and practitioners directly involved in deploying technology in FSC, the study emphasizes several consequences. The current study provides valuable insights for managers of FSC businesses in developing nations. Practitioners and management can utilize a comprehensive framework containing a full list of barriers relevant to AI adoption in the FSC. Policymakers, decision-makers, and organizational managers can benefit from creating effective plans and guidelines for implementing AI technology, considering factors such as the time required, necessary infrastructure, and knowledge and training services for successful adoption. The study's results indicate that the adoption of AI in FSC businesses can be facilitated by sequentially overcoming important barriers, including technological maturity, adequate security and privacy, competitive pressure, regulatory and compliance requirements, and perceived benefits. These findings align with those of Dora et al. (2022) and Tsolakis et al. [22], who stated that the adoption of AI technologies depends on factors such as technological preparedness, including access to trained human resources and a solid infrastructure. FSC businesses can use AI technology to enhance operational efficiencies by providing real-time tracking information to minimize various shipping-related issues. The use of AI technology in food supply chain businesses significantly enhances operational efficiencies by offering real-time tracking information. This capability allows companies to monitor shipments accurately, ensuring timely deliveries and reducing the risk of spoilage or delays. As a result, AI helps minimize various shipping-related issues, leading to improved reliability and customer satisfaction.

For respondent companies, the tools and preliminary study offered here provide suitable resources to discover essential barriers and optimal paths for overcoming them. The incremental barrier addressing method may be the only workable option to develop a more comprehensive AI adoption. Respondent companies can achieve the best results by selecting a combination of barriers based on their understanding and resources. There may be more than one adaptive path to accomplish the objective, and this allows for some flexibility, especially when the number of other barriers rises. With six barriers, there could be an estimated 2^6 potential combinations. This strategy is endorsed by the practice literature on green management, with the usual justification being to identify high-yield, quick gains [74]

5. Conclusion limitation and future scope

AI adoption in the FSC has been recognized as a significant approach for the industry to develop sustainable and efficient processes, enhancing overall food distribution and logistics. A primary concern revolves around leading organizations in prioritizing tasks and gradually removing obstacles to AI adoption, allowing them to operate optimally by choosing the best course of action. The research proposes a DEMATEL-NK method to identify and visualize the optimal path around obstacles to AI applications in FSC. Specifically, the NK model and DEMATEL-based theoretical framework are employed to determine the best path for overcoming AI adoption barriers through simulation and structural modeling techniques. Methodologically, two approaches are used: firstly, extending the traditional DEMATEL method to handle information with asymmetric preferences, and secondly, utilizing DEMATEL to mine different causal interdependencies across AI adoption barriers to rectify the classical NK model. Results indicate that barriers related to technological maturity, adequate security and privacy, competitive pressure, regulatory and compliance requirements, and perceived benefits should be mitigated with high priority in AI adoption. The identified optimum path findings link barriers to be overcome in distinct phases based on causal relationships, potentially achieving a high-return FSC level and saving significant management resources.

This sample contributes to the method's validation and justification. However, to evaluate the broader industry insights and general consequences, a more extensive examination is still required. Real implementations supporting the study would reinforce its validity. Extending the study's reach could also benefit from incorporating and applying alternative decision-making techniques. Intangibility appraisals and alternative methods, such as "grey" and "fuzzy" system theory, can address the ambiguity in human subjective evaluations serving as valuable tools for management. These areas seem worthwhile for further research. While this study has some limitations, there is an opportunity to explore how this tool can increase AI adoption in the FSC. Suggestions for future research and development directions have been provided as the issue continues to evolve within developing and developed industries and regions. Evaluating how organizations adjust and identify dynamic decision settings will be crucial as this issue grows.

CRediT authorship contribution statement

Nikhil Ghag: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Harshad Sonar:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sandeep Jagtap:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Resources, Funding acquisition. **Hana Trollman:** Writing – review & editing, Writing – original draft, Supervision, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jafr.2024.101349.

Appendix

A1
Direct relationship Matrix of Technology barrier

	T1	T2	T3	T4
T1	1	2	2	2
T2	3	1	2	1
T3	2	2	1	1
T4	2	2	3	1

A2
Direct relationship Matrix of Social Economic barrier

	S1	S2	S3	S4	S5	S6
S1	1	2	2	2	2	2
S2	3	1	2	2	2	2
S3	3	3	1	2	3	2
S4	2	2	2	1	2	1
S5	2	2	2	2	1	1
S6	1	2	2	2	3	1

A3
Direct relationship Matrix of Environmental barrier

	En1	En2	En3	En4	En5
En1	1	3	1	2	1
En2	2	1	1	2	2
En3	2	2	1	1	2
En4	2	1	1	1	1
En5	2	2	1	1	1

A4
Normalized Matrix of Technology Barrier

	T1	T2	T3	T4
T1	0.125	0.25	0.25	0.25
T2	0.375	0.125	0.25	0.125
T3	0.25	0.25	0.125	0.125
T4	0.25	0.25	0.375	0.125

A5
Normalized Matrix of Social-Economic Barrier

	S1	S2	S3	S4	S5	S6
S1	0.071429	0.142857	0.142857	0.142857	0.142857	0.142857
S2	0.214286	0.071429	0.142857	0.142857	0.142857	0.142857
S3	0.214286	0.214286	0.071429	0.142857	0.214286	0.142857
S4	0.142857	0.142857	0.142857	0.071429	0.142857	0.071429
S5	0.142857	0.142857	0.142857	0.142857	0.071429	0.071429
S6	0.071429	0.142857	0.142857	0.142857	0.214286	0.071429

A6
Normalized Matrix of Environmental Barrier

	En1	En2	En3	En4	En5
En1	0.125	0.375	0.125	0.25	0.125
En2	0.25	0.125	0.125	0.25	0.25
En3	0.25	0.25	0.125	0.125	0.25
En4	0.25	0.125	0.125	0.125	0.125
En5	0.25	0.25	0.125	0.125	0.125

A7
Total Relationship matrix of Technology Barrier

	T1	T2	T3	T4
T1	1.7342	1.6608	1.8025	1.2759
T2	1.9241	1.5316	1.7722	1.1646
T3	1.6203	1.4582	1.4608	1.0228
T4	2.0253	1.8228	2.0759	1.2785

A8
Total Relationship matrix of Social-Economic Barrier

	S1	S2	S3	S4	S5	S6
S1	0.6692	0.7264	0.681	0.681	0.7654	0.5846
S2	0.8472	0.7082	0.7264	0.7264	0.8164	0.6236
S3	0.9497	0.9339	0.7506	0.8172	0.9804	0.6974
S4	0.6912	0.6782	0.6358	0.5692	0.7105	0.4838
S5	0.6912	0.6782	0.6358	0.6358	0.6438	0.4838
S6	0.6707	0.7232	0.678	0.678	0.824	0.5112

A9
Total Relationship matrix of Environmental Barrier

	En1	En2	En3	En4	En5
En1	3.1291	3.392	1.8226	2.7628	2.4745
En2	3.209	3.1517	1.8051	2.7252	2.5497
En3	3.2943	3.362	1.853	2.6851	2.6299
En4	2.5271	2.4694	1.4215	2.0461	1.9079
En5	2.9282	2.9884	1.6471	2.3867	2.2266

A10
Fitness Values for Environment barriers

Genome					EN1	EN2	EN3	EN4	EN5	Fitness	Rank	Path
0	0	0	0	0	0	0	0	0	0	0		
0	0	0	0	1	0	0	0	0	0.111119	0.111119		
0	0	0	1	0	0	0	0	0.43887	0	0.43887		
0	0	1	0	0	0	0	0.979748	0	0	0.979748	1	EN3
0	1	0	0	0	0	0.904881	0	0	0	0.904881		
1	0	0	0	0	0.184816	0	0	0	0	0.184816		
0	0	1	0	1	0	0	0.979748	0	0.111119	1.090868		
0	0	1	1	0	0	0	0.979748	0.43887	0	1.418618		
0	0	0	1	1	0	0	0	0.43887	0.111119	0.549989		
0	1	0	0	1	0	0.904881	0	0	0.111119	1.016		
0	1	0	1	0	0	0.904881	0	0.43887	0	1.343751		
0	1	1	0	0	0	0.904881	0.979748	0	0	1.884629	2	EN2
1	0	0	0	1	0.184816	0	0	0	0.111119	0.295936		
1	0	0	1	0	0.184816	0	0	0.43887	0	0.623686		
1	0	1	0	0	0.184816	0	0.979748	0	0	1.164565		
1	1	0	0	0	0.184816	0.904881	0	0	0	1.089697		
0	0	1	1	1	0	0	0.979748	0.43887	0.111119	1.529738		
0	1	0	1	1	0	0.904881	0	0.43887	0.111119	1.45487		
0	1	1	0	1	0	0.904881	0.979748	0	0.111119	1.995749		
1	0	0	1	1	0.184816	0	0	0.43887	0.111119	0.734806		
0	1	1	1	0	0	0.904881	0.979748	0.43887	0	2.323499	3	EN4
1	0	1	0	1	0.184816	0	0.979748	0	0.111119	1.275684		
1	0	1	1	0	0.184816	0	0.979748	0.43887	0	1.603435		
1	1	1	0	0	0.184816	0.904881	0.979748	0	0	2.069446		
1	1	0	0	1	0.184816	0.904881	0	0	0.111119	1.200817		
1	1	0	1	0	0.184816	0.904881	0	0.43887	0	1.528567		
1	0	1	1	1	0.184816	0	0.979748	0.43887	0.111119	1.714554		
1	1	0	1	1	0.184816	0.904881	0	0.43887	0.111119	1.200817		
0	1	1	1	1	0	0.904881	0.979748	0.43887	0.111119	2.434619	4	EN5
1	1	1	0	1	0.184816	0.904881	0.979748	0	0.111119	2.180565		
1	1	1	1	0	0.184816	0.904881	0.979748	0.43887	0	2.069446		
1	1	1	1	1	0.184816	0.904881	0.979748	0.43887	0.111119	2.619435	5	EN1

A11
Fitness Values for Socia-economic barriers

						S1	S2	S3	S4	S5	S6	Fitness	Rank	Path
0	0	0	0	0	0	0	0	0	0	0	0	0		
0	0	0	0	0	1	0	0	0	0	0	0.498094	0.498094		
0	0	0	0	1	0	0	0	0	0	0.227843	0	0.227843		
0	0	0	1	0	0	0	0	0	0.801348	0	0	0.801348		
0	0	1	0	0	0	0	0	0.479523	0	0	0	0.479523		
0	1	0	0	0	0	0	0.52768	0	0	0	0	0.52768		
1	0	0	0	0	0	0.98995	0	0	0	0	0	0.98995	1	SO1
0	0	0	0	1	1	0	0	0	0	0.227843	0.498094	0.725937		
0	0	0	1	0	1	0	0	0	0.801348	0	0.498094	1.299442		
0	0	1	0	0	1	0	0	0.479523	0	0	0.498094	0.977618		
0	0	0	1	1	0	0	0	0	0.801348	0.227843	0	1.029191		
0	0	1	0	1	0	0	0	0.479523	0	0.227843	0	0.707366		
0	0	1	1	0	0	0	0	0.479523	0.801348	0	0	1.280871		
0	1	0	0	0	1	0	0.52768	0	0	0	0.498094	1.025774		
0	1	0	0	1	0	0	0.52768	0	0	0.227843	0	0.755523		
0	1	0	1	0	0	0	0.52768	0	0.801348	0	0	1.329028		
0	1	1	0	0	0	0	0.52768	0.479523	0	0	0	1.007203		
1	0	0	0	0	1	0.98995	0	0	0	0	0.498094	1.488044		
1	0	0	0	1	0	0.98995	0	0	0	0.227843	0	1.217793		
1	0	0	1	0	0	0.98995	0	0	0.801348	0	0	1.791298		
1	0	1	0	0	0	0.98995	0	0.479523	0	0	0	1.469474		
1	1	0	0	0	0	0.98995	0.52768	0	0	0	0	1.51763	2	SO2
0	0	0	1	1	1	0	0	0	0.801348	0.227843	0.498094	1.527285		
0	0	1	0	1	1	0	0	0.479523	0	0.227843	0.498094	1.205461		
0	0	1	1	0	1	0	0	0.479523	0.801348	0	0.498094	1.778965		
0	0	1	1	1	0	0	0	0.479523	0.801348	0.227843	0	1.508714		
0	1	0	0	1	1	0	0.52768	0	0	0.227843	0.498094	1.253617		
0	1	0	1	0	1	0	0.52768	0	0.801348	0	0.498094	1.827122		
0	1	0	1	1	0	0	0.52768	0	0.801348	0.227843	0	1.556871		
0	1	1	0	0	1	0	0.52768	0.479523	0	0	0.498094	1.505298		
0	1	1	0	1	0	0	0.52768	0.479523	0	0.227843	0	1.235046		
0	1	1	1	0	0	0	0.52768	0.479523	0.801348	0	0	1.808551		
1	0	0	0	1	1	0.98995	0	0	0	0.227843	0.498094	1.715887		
1	0	0	1	0	1	0.98995	0	0	0.801348	0	0.498094	2.289392		
1	0	0	1	1	0	0.98995	0	0	0.801348	0.227843	0	2.019141		
1	0	1	0	0	1	0.98995	0	0.479523	0	0	0.498094	1.967568		
1	0	1	0	1	0	0.98995	0	0.479523	0	0.227843	0	1.697317		
1	0	1	1	0	0	0.98995	0	0.479523	0.801348	0	0	2.270821		
1	1	1	0	0	0	0.98995	0.52768	0.479523	0	0	0	1.997154		
1	1	0	0	0	1	0.98995	0.52768	0	0	0	0.498094	2.015725		
1	1	0	0	1	0	0.98995	0.52768	0	0	0.227843	0	1.745473		
1	1	0	1	0	0	0.98995	0.52768	0	0.801348	0	0	2.318978	3	SO4
0	1	0	1	1	1	0	0.52768	0	0.801348	0.227843	0.498094	2.054965		
0	1	1	0	1	1	0	0.52768	0.479523	0	0.227843	0.498094	1.733141		
0	1	1	1	0	1	0	0.52768	0.479523	0.801348	0	0.498094	2.306645		
0	1	1	1	1	0	0	0.52768	0.479523	0.801348	0.227843	0	2.036394		
1	0	1	0	1	1	0.98995	0	0.479523	0	0.227843	0.498094	2.195411		
1	0	1	1	0	1	0.98995	0	0.479523	0.801348	0	0.498094	2.768915		
1	0	1	1	1	0	0.98995	0	0.479523	0.801348	0.227843	0	2.498664		
1	1	0	0	1	1	0.98995	0.52768	0	0	0.227843	0.498094	2.243568		
1	1	0	1	0	1	0.98995	0.52768	0	0.801348	0	0.498094	2.817072	4	SO6
1	1	0	1	1	0	0.98995	0.52768	0	0.801348	0.227843	0	2.546821		
1	1	1	0	0	1	0.98995	0.52768	0.479523	0	0	0.498094	2.495248		
1	1	1	0	1	0	0.98995	0.52768	0.479523	0	0.227843	0	2.224997		
1	1	1	1	0	0	0.98995	0.52768	0.479523	0.801348	0	0	2.798501		
1	0	0	1	1	1	0.98995	0	0	0.801348	0.227843	0.498094	2.517235		
0	0	1	1	1	1	0	0	0.479523	0.801348	0.227843	0.498094	2.006808		
0	1	1	1	1	1	0	0.52768	0.479523	0.801348	0.227843	0.498094	2.534488		
1	0	1	1	1	1	0.98995	0	0.479523	0.801348	0.227843	0.498094	2.996758		
1	1	0	1	1	1	0.98995	0.52768	0	0.801348	0.227843	0.498094	3.044915		
1	1	1	0	1	1	0.98995	0.52768	0.479523	0	0.227843	0.498094	2.723091		
1	1	1	1	0	1	0.98995	0.52768	0.479523	0.801348	0	0.498094	3.296596	5	SO3
1	1	1	1	1	0	0.98995	0.52768	0.479523	0.801348	0.227843	0	3.026344		
1	1	1	1	1	1	0.98995	0.52768	0.479523	0.801348	0.227843	0.498094	3.524438	6	SO5

References

[1] P. Weill, S.L. Woerner, Is your company ready for a digital future? MIT Sloan Manag. Rev. 59 (2) (2018) 21–25.

[2] E.M. El Bhilat, A. El Jaouhari, L.S. Hamidi, Assessing the influence of artificial intelligence on agri-food supply chain performance: the mediating effect of distribution network efficiency, Technol. Forecast. Soc. Change 200 (2024) 123149.

[3] S. Akter, K. Michael, M.R. Uddin, et al., Transforming business using digital innovations: the application of AI, blockchain, cloud and data analytics, Ann. Oper. Res. 308 (1–2) (2022) 7–39. Springer US.

[4] N.R. Sanders, T. Boone, R. Ganeshan, et al., Sustainable supply chains in the age of AI and digitization: research challenges and opportunities, J. Bus. Logist. 40 (3) (2019) 229–240.

[5] J. Bughin, J. Seong, J. Manyika, et al., Notes from the ai frontier: modeling the impact of ai on the world economy, Modeling the global economic impact of AI | McKinsey (September) (2018) 1–61.
[6] ResearchAndMarkets, Artificial Intelligence in the Global Food & Beverages Market - Forecasting Astronomical Growth at a CAGR of 45, 2021, 77% from 2021 to 2026.
[7] A. Belhadi, V. Mani, S.S. Kamble, et al., Artificial intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: an empirical investigation, in: Annals of Operations Research (0123456789). Springer US. Epub Ahead of Print 2021, 2021, https://doi.org/10.1007/s10479-021-03956-x.
[8] R. Dubey, A. Gunasekaran, S.J. Childe, et al., Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: a study of manufacturing organisations, Int. J. Prod. Econ. 226 (December 2019) (2020) 107599. Elsevier B.V.
[9] D. Mishra, K. Muduli, R. Raut, B.E. Narkhede, H. Shee, S.K. Jana, Challenges facing artificial intelligence adoption during COVID-19 pandemic: an investigation into the agriculture and agri-food supply chain in India, Sustainability 15 (8) (2023), https://doi.org/10.3390/su15086377.
[10] K. Govindan, S.G. Azevedo, H. Carvalho, et al., Lean, green and resilient practices influence on supply chain performance: interpretive structural modeling approach, Int. J. Environ. Sci. Technol. 12 (1) (2015) 15–34.
[11] T. Papadopoulos, A. Gunasekaran, R. Dubey, et al., The role of Big Data in explaining disaster resilience in supply chains for sustainability, J. Clean. Prod. 142 (2017) 1108–1118. Elsevier Ltd.
[12] G. Baryannis, S. Validi, S. Dani, et al., Supply chain risk management and artificial intelligence: state of the art and future research directions, Int. J. Prod. Res. 57 (7) (2019) 2179–2202.
[13] B. Shen, T.M. Choi, S. Minner, A review on supply chain contracting with information considerations: information updating and information asymmetry, Int. J. Prod. Res. 57 (15–16) (2019) 4898–4936.
[14] S. Chen, S. Brahma, J. Mackay, et al., The role of smart packaging system in food supply chain, J. Food Sci. 85 (3) (2020) 517–525.
[15] M. Dora, J. Wesana, X. Gellynck, et al., Importance of sustainable operations in food loss: evidence from the Belgian food processing industry, Ann. Oper. Res. 290 (1–2) (2020) 47–72. Springer US.
[16] S. Jagtap, H. Trollman, F. Trollman, G. Garcia-Garcia, W. Martindale, Surviving the storm: navigating the quadruple whammy impact on europe's food supply chain, Int. J. Food Sci. Technol. 59 (6) (2024) 3652–3666.
[17] P. Kittipanya-ngam, K.H. Tan, A framework for food supply chain digitalization: lessons from Thailand, Prod. Plann. Control 31 (2–3) (2020) 158–172. Taylor & Francis.
[18] Gartner, Top trends in the gartner hype cycle for emerging technologies, Available at: https://www.gartner.com/smarter%0Awithgartner/top-trends-in-the-gartner-hype-cycle-for-emerging-technologies-2017, 2017. (Accessed 4 November 2023).
[19] Haoyang Wu, Huaili Wu, M. Zhu, et al., A new method of large-scale short-term forecasting of agricultural commodity prices: illustrated by the case of agricultural markets in Beijing, Journal of Big Data 4 (1) (2017) 1–22. Springer International Publishing.
[20] L.W. Wong, L.Y. Leong, J.J. Hew, et al., Time to seize the digital evolution: adoption of blockchain in operations and supply chain management among Malaysian SMEs, Int. J. Inf. Manag. 52 (March 2019) (2020) 101997. Elsevier.
[21] A.K. Sharma, M.K. Srivastava, R. Sharma, Exposition of techno-functional components of intelligent food supply chain: a review and future research agenda, J. Bus. Ind. Market. (2024), https://doi.org/10.1108/JBIM-10-2023-0582.
[22] N. Tsolakis, R. Schumacher, M. Dora, M. Kumar, Artificial intelligence and blockchain implementation in supply chains: a pathway to sustainability and data monetisation? Ann. Oper. Res. 327 (1) (2023) 157–210.
[23] R.C.H. Denny, S.T. Marquart-Pyatt, A. Ligmann-Zielinska, et al., Food security in Africa: a cross-scale, empirical investigation using structural equation modeling, Environment Systems and Decisions 38 (1) (2018) 6–22. Springer US.
[24] S. Mohan, M. Gopalakrishnan, P.J. Mizzi, Improving the efficiency of a non-profit supply chain for the food insecure, Int. J. Prod. Econ. 143 (2) (2013) 248–255. Elsevier.
[25] K. Behnke, M.F.W.H.A. Janssen, Boundary conditions for traceability in food supply chains using blockchain technology, Int. J. Inf. Manag. 52 (2020) 101969. Elsevier.
[26] S. Verma, S.S. Bhattacharyya, Perceived strategic value-based adoption of Big Data Analytics in emerging economy: a qualitative approach for Indian firms, J. Enterprise Inf. Manag. 30 (3) (2017) 354–382.
[27] E. Yadegaridehkordi, M. Hourmand, M. Nilashi, et al., Influence of big data adoption on manufacturing companies' performance: an integrated DEMATEL-ANFIS approach, Technol. Forecast. Soc. Change 137 (March) (2018) 199–210.
[28] K. Spanaki, E. Karafili, U. Sivarajah, et al., Artificial intelligence and food security: swarm intelligence of AgriTech drones for smart AgriFood operations, Prod. Plann. Control 33 (16) (2022) 1498–1516. Taylor & Francis.
[29] S. Sun, C.G. Cegielski, L. Jia, et al., Understanding the factors affecting the organizational adoption of big data, J. Comput. Inf. Syst. 58 (3) (2018) 193–203. Taylor & Francis.
[30] S. Saberi, M. Kouhizadeh, J. Sarkis, et al., Blockchain technology and its relationships to sustainable supply chain management, Int. J. Prod. Res. 57 (7) (2019) 2117–2135.
[31] Y. Duan, M. Miao, R. Wang, et al., A framework for the successful implementation of food traceability systems in China, Inf. Soc. 33 (4) (2017) 226–242. Routledge.
[32] Z. Alreemy, V. Chang, R. Walters, et al., Critical success factors (CSFs) for information technology governance (ITG), Int. J. Inf. Manag. 36 (6) (2016) 907–916. Elsevier Ltd.
[33] R. Hentschel, C. Leyh, T. Baumhauer, Critical success factors for the implementation and adoption of cloud services in SMEs. *Proceedings Of the Annual Hawaii International Conference On System Sciences* 2019-Janua, 2019, pp. 7342–7351.
[34] H. Gangwar, H. Date, R. Ramaswamy, Understanding determinants of cloud computing adoption using an integrated TAM-TOE model, J. Enterprise Inf. Manag. 28 (1) (2015) 107–130.
[35] M. Tu, An exploratory study of internet of things (IoT) adoption intention in logistics and supply chain management a mixed research approach, Int. J. Logist. Manag. 29 (1) (2018) 131–151.
[36] A. Gunasekaran, Y.Y. Yusuf, E.O. Adeleye, et al., Agile manufacturing practices: the role of big data and business analytics with multiple case studies, Int. J. Prod. Res. 56 (1–2) (2018) 385–397. Taylor & Francis.
[37] M. Abolghasemi, E. Beh, G. Tarr, et al., Demand forecasting in supply chain: the impact of demand volatility in the presence of promotion, Comput. Ind. Eng. 142 (February) (2020) 106380. Elsevier.
[38] A. Tayal, A. Solanki, R. Kondal, et al., Blockchain-based efficient communication for food supply chain industry: transparency and traceability analysis for sustainable business, Int. J. Commun. Syst. 34 (4) (2021). John Wiley and Sons Ltd.
[39] M. Esther, M. Sharon, C.V.K. Abirami, et al., Grain storage management in India, Journal of Postharvest Technology 2 (1) (2014) 12–22.
[40] A. Chauhan, H. Kaur, S. Yadav, et al., A hybrid model for investigating and selecting a sustainable supply chain for agri-produce in India, Ann. Oper. Res. 290 (1–2) (2020) 621–642. Springer.
[41] A. Fredriksson, K. Liljestrand, Capturing food logistics: a literature review and research agenda, Int. J. Logist. Res. Appl. 18 (1) (2015) 16–34. Taylor and Francis Ltd.
[42] C. Göbel, N. Langen, A. Blumenthal, et al., Cutting food waste through cooperation along the food supply chain, Sustainability 7 (2) (2015) 1429–1445. MDPI.
[43] M. Rahman, M.M. Kamal, E. Aydin, et al., Impact of Industry 4.0 drivers on the performance of the service sector: comparative study of cargo logistic firms in developed and developing regions, Prod. Plann. Control 33 (2–3) (2022) 228–243. Taylor & Francis.
[44] S. Kumari, V.G. Venkatesh, F.T.C. Tan, S.V. Bharathi, M. Ramasubramanian, Y. Shi, Application of machine learning and artificial intelligence on agriculture supply chain: a comprehensive review and future research directions, Ann. Oper. Res. (2023), https://doi.org/10.1007/s10479-023-05556-3.
[45] P.S. Sutar, G. Kolte, S. Yamini, K. Mathiyazhagan, Food supply chain resilience in the digital era: a bibliometric analysis and development of conceptual framework, J. Bus. Ind. Market. (2024), https://doi.org/10.1108/JBIM-10-2023-0587.
[46] I.J. Orji, S. Kusi-Sarpong, H. Gupta, The critical success factors of using social media for supply chain social sustainability in the freight logistics industry, Int. J. Prod. Res. 58 (5) (2020) 1522–1539. Taylor & Francis.
[47] A.M. Elbaz, M.Y. Haddoud, The role of wisdom leadership in increasing job performance: evidence from the Egyptian tourism sector, Tourism Manag. 63 (2017) 66–76. Elsevier Ltd.
[48] K. Ramamurthy, Ram, A. Sen, A.P. Sinha, An empirical investigation of the key determinants of data warehouse adoption, Decis. Support Syst. 44 (4) (2008) 817–841.
[49] E. Yadegaridehkordi, M. Hourmand, M. Nilashi, et al., Influence of big data adoption on manufacturing companies' performance: an integrated DEMATEL-ANFIS approach, Technol. Forecast. Soc. Change 137 (July) (2018) 199–210.
[50] T. Bahmanziari, J.M. Pearson, L. Crosby, Is trust important in technology adoption? A policy capturing approach, J. Comput. Inf. Syst. 43 (4) (2003) 46–54.
[51] M.M. Queiroz, S. Fosso Wamba, Blockchain adoption challenges in supply chain: an empirical investigation of the main drivers in India and the USA, Int. J. Inf. Manag. 46 (2019) 70–82. Elsevier Ltd.
[52] N. Tsolakis, D. Niedenzu, M. Simonetto, et al., Supply network design to address United Nations Sustainable Development Goals: a case study of blockchain implementation in Thai fish industry, J. Bus. Res. 131 (2021). Elsevier Inc.: 495–519.
[53] N.&K.S. Viswanadham, Ecosystem-Aware Global Supply Chain Management, 2013.
[54] R.K. Singh, S. Luthra, S.K. Mangla, et al., Applications of information and communication technology for sustainable growth of SMEs in India food industry, Resour. Conserv. Recycl. 147 (January) (2019) 10–18. Elsevier.
[55] S. Luthra, S.K. Mangla, Evaluating challenges to Industry 4.0 initiatives for supply chain sustainability in emerging economies, Process Saf. Environ. Protect. 117 (2018) 168–179. Institution of Chemical Engineers.
[56] C. Bai, A. Satir, Barriers for green supplier development programs in manufacturing industry, Resour. Conserv. Recycl. 158 (March) (2020) 104756. Elsevier.
[57] W. Song, Y. Zhu, Q. Zhao, Analyzing barriers for adopting sustainable online consumption: a rough hierarchical DEMATEL method, Comput. Ind. Eng. 140 (37) (2020) 106279. Elsevier.
[58] C.P. Garg, Modeling the e-waste mitigation strategies using grey-theory and DEMATEL framework, J. Clean. Prod. 281 (2021) 124035. Elsevier Ltd.
[59] A. Gabus, E. Fontela, Perceptions of the World Problematique: Communication Procedure, Communicating with Those Bearing Collective Responsibility, 1973. Epub ahead of print 1973.
[60] E. Fontela, A. Gabus, The DEMATEL Observer: Battelle Institute, 1976, pp. 56–61. Geneva Research Center.

[61] S.A. Kauffman, E.D. Weinberger, The NK model of rugged fitness landscapes and its application to maturation of the immune response, J. Theor. Biol. 141 (2) (1989) 211–245.

[62] G. Dosi, M. Faillo, L. Marengo, D. Moschella, Modeling routines and organizational learning: a discussion of the state-of-the-art, in: LEM Working Paper Series. 2011/04, 2011.

[63] I.Y.H. Fan, R.W.B. Lee, Design of a weighted and informed NK model for intellectual capital-based innovation planning, Expert Syst. Appl. 39 (10) (2012) 9222–9229. Elsevier Ltd.

[64] C. Bai, J. Sarkis, Y. Dou, Constructing a process model for low-carbon supply chain cooperation practices based on the DEMATEL and the NK model, Supply Chain Manag. 22 (3) (2017) 237–257.

[65] N.S. Ghag, P. Acharya, V. Khanapuri, Sustainable competitiveness practices of SMEs: a strategic framework using integrated DEMATEL-NK model, Journal of Global Operations and Strategic Sourcing (February 2023 (2022), https://doi.org/10.1108/JGOSS-06-2022-0064. Epub ahead of print 2022.

[66] H. Sun, W. Mao, Y. Dang, et al., Optimum path for overcoming barriers of green construction supply chain management: a grey possibility DEMATEL-NK approach, Comput. Ind. Eng. 164 (October 2021) (2022) 107833. Elsevier Ltd.

[67] K. Oyama, G. Learmonth, R. Chao, Applying complexity science to new product development: modeling considerations, extensions, and implications, Journal of Engineering and Technology Management - JET-M 35 (2015) 1–24. Elsevier B.V.

[68] Robert K. Yin, Case Study Research and Applications: Design and Methods, 2017. Epub ahead of print 2017.

[69] Y. Yin, K.E. Stecke, M. Swink, et al., Lessons from seru production on manufacturing competitively in a high cost environment, J. Oper. Manag. 49–51 (2017) 67–76. Elsevier Ltd.

[70] M. Ketokivi, T. Choi, Renaissance of case research as a scientific method, J. Oper. Manag. 32 (5) (2014) 232–240. Elsevier B.V.

[71] Z. Yang, J. Sun, Y. Zhang, Y. Wang, Understanding SaaS adoption from the perspective of organizational users: a tripod readiness model, Comput. Hum. Behav. 45 (2015) 254–264.

[72] A.M. Aamer, M.A. Al-Awlaqi, I. Affia, et al., The internet of things in the food supply chain: adoption challenges, Benchmark Int. J. 28 (8) (2021) 2521–2541.

[73] L.G. Tornatzky, M. Fleischer, A.K. Chakrabarti, The Processes of Technological Innovation. (No Title), 1990. Epub ahead of print 1990.

[74] J.J. Flaig, Improving project selection using expected net present value analysis, Qual. Eng. 17 (4) (2005) 535–538.