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Integration of industry 4.0 technologies for agri-food supply chain resilience

Rohit Sharma [a,b,*], Balan Sundarakani [b], Ioannis Manikas [c]

[a] Marketing, Operations, and Information Systems, College of Business, Abu Dhabi University, PO Box 1790, Al Ain, United Arab Emirates
[b] School of Business, University of Wollongong in Dubai, Knowledge Park, Dubai 20183, United Arab Emirates
[c] Czech University of Life Sciences Prague (CZU), Faculty of Agrobiology, Food and Natural Resources, Kamýcká 129, Praha – Suchdol 165 00, Czech Republic

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ABSTRACT

The agri-food supply chain (AFSC) operations are becoming challenging due to globalization, constantly shifting consumer demands, and intensive disruptions leading to inefficient production and distribution of safe and high-quality food. Technological advancements are the most promising ways to ensure firms' survival and supply chains. To enhance the resilience of AFSCs, the present study aims to identify and model the challenges associated with AFSC operations in the context of the United Arab Emirates (UAE) food processing industry. An integrated methodology using the Grey Influence Analysis (GINA) and Fuzzy Linguistic Quantifier Ordered Weighted Aggregation (FLQOWA) methodology is applied to analyze resilience enablers and assess industry 4.0 technologies (I4Ts) that can enhance resilience in AFSCs. The GINA technique helps identify the most influential resilience enablers, and the FLQOWA helps assess and prioritize I4Ts to enhance resilient enablers. The findings reveal that out of thirteen sub-enablers, four are the most influential resilient enablers, viz., real-time information sharing, enhanced product traceability, improved risk management, and planning and network design; and out of ten I4Ts, three are the most influential technologies viz., big data analytics, Internet of things, and cloud computing can further enhance resilience enablers. The findings from the study can help AFSC organizations and the government formulate appropriate strategies based on the integrated matrix developed by selecting the best combination of technologies for strengthening the required resilient enablers among the AFSC stakeholders.

1. Introduction

Over the last few years, global supply chains are constantly under pressure due to disruptive events such as the COVID-19 pandemic, geopolitical events/unrest, the '*Evergreen*' saga in the Suez Canal, the global chip shortage, global cyber vulnerabilities, and human-induced climate change. COVID-19 left such an unprecedented effect on the global supply chains that many businesses had to shut down their operations, and many are still improvising their business models towards recovery and growth (Carracedo et al., 2021; Dohale et al., 2022; Donthu and Gustafsson, 2020; El Baz and Ruel, 2021; Ivanov and Dolgui, 2021a; Meyer et al., 2022; Nagurney, 2021; Narayanamurthy and Tortorella, 2021; Seetharaman, 2020; Verma and Gustafsson, 2020). These disruptions adversely impacted the performance of the organizations, i.e., shipment and delivery delays, demand and supply fluctuations, port congestions, and other structural factors, which in turn affected sustainable performance (Butt, 2021; Raj et al., 2022). All these disruptions have negatively impacted the agri-food supply chains (AFSCs), which are essential for feeding the next ten billion by 2050.[1] At the current pace, using the present technologies in agriculture, an additional 70 % more food is to be produced to sustain the future populations, which will further pressurize already resource-constrained AFSCs (Sharma et al., 2022a).

Under these acute disruptions, supply chain resilience strategies are essential to safely navigating through turbulent global scenarios. A lot of *post-pandemic literature* on supply chain resilience has gained much attention from academia and the industry (Golan et al., 2021; Modgil et al., 2021; Moosavi and Hosseini, 2021; Shen and Sun, 2023; Spieske and Birkel, 2021). Supply chain resilience is defined as "*the capability of the supply chains to bounce back in their improved settings of original state*

* Corresponding author at: Marketing, Operations, and Information Systems, College of Business, Abu Dhabi University, PO Box 1790, Al Ain, United Arab Emirates.

E-mail addresses: Rohit.sharma@adu.ac.ae (R. Sharma), balansundarakani@uowdubai.ac.ae (B. Sundarakani), manikas@af.czu.cz (I. Manikas).

[1] https://www.eitfood.eu/blog/sustainably-feeding-the-world-in-2050-are-efficiency-and-equity-the-answer

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0166-3615/© 2024 Elsevier B.V. All rights reserved, including those for text and data mining, AI training, and similar technologies.

post disruption" (Christopher and Peck, 2004; Shishodia et al., 2023). There have been many supply chain disruptions, but none matched the severity of the COVID-19 pandemic as it was a black swan event. Therefore, AFSCs and agribusiness industries were unprepared for this uncertain risk (owing to different agri-climatic zones) and the unique challenges arising from this disruption and their impacts (Sharma et al., 2020b). In the case of the United Arab Emirates (UAE), the climate is not favourable for large-scale food production, thereby making it heavily import-dependent[2] (agricultural and agriculture-related imports were valued at USD 14.6 billion in 2020). Many food processing organizations (predominantly small and medium enterprises) in the UAE rely heavily on food imports (raw, semi-processed, and finished products) to enhance self-sufficiency and food security. The UAE also invests in modern Industry 4.0 technologies (I4Ts) to ensure sustainability and food security. As far as supply chain resilience is concerned, collaboration among various firms in the value chain improves resiliency through real-time information exchange and risk mitigation strategies (da Silva Poberschnigg et al., 2020; Dubey et al., 2020; Scholten and Schilder, 2015; Tukamuhabwa et al., 2015). The need for AFSC resilience results from global environmental, social, and economic crises that have radically changed the AFSCs and rendered them complex and fragile. The ultimate goal of AFSC resilience is to ensure quick recovery during a crisis. For instance, countries relying heavily on food imports, recent disruptive events caused by geopolitical tensions, social unrest, and armed conflicts in the Red Sea have severely impacted the resilience of their AFSCs (Notteboom et al., 2024; Srai et al., 2023). In present times, AFSC resilience is more emphasized as compared to the past AFSCs, wherein they were designed to be economically efficient, but now, the focus has shifted to reducing growing vulnerability and volatility and re-evaluating resilience.

Previous studies have highlighted that I4Ts are anticipated to improve the resiliency and sustainability of the AFSCs and, in turn, make them robust (Qader et al., 2022; Razak et al., 2021). Despite I4Ts' advantages for the AFSCs, limited studies have explored the linkages between I4Ts and AFSC resilience in the UAE and Middle East and North Africa (MENA) regions.

Keeping in mind the perspectives mentioned above, the present study is carried out to address the following research questions (RQs):

***RQ1:** What are the most influential resilient enablers in AFSCs?*

***RQ2:** Which potential I4Ts enhance the resilient enablers of AFSCs?*

While the RQs primarily target the UAE and the MENA regions, it is crucial to remember that the core issues they address are critical to the AFSCs of other countries as well. In this context, we highlight the importance of resilience in the modern AFSCs. As modern agricultural operations are heavily data intensive, we make use of the I4Ts, highlighting the data-driven approach in the AFSCs. The present study follows an integrated research methodology, i.e., in the first step, a systematic literature review was carried out to find out the enablers for creating resilient AFSCs. After the enablers were identified, analysis of causal relationships among the identified enablers was done using Grey Influence Analysis (GINA) technique (Rajesh, 2023). Subsequently, Fuzzy Linguistic Quantifier Ordered Weighted Aggregation (FLQOWA) was applied to assess the appropriate I4T for enhancing the identified resilience enablers. In the second step, a survey-based questionnaire was shared with industry practitioners (from the processing and packaging industry) to seek their input. The responses were then investigated using the GINA technique, and the results were analyzed. Finally, for the FLQOWA technique, the experts were asked to rate each I4T against the identified enablers for improving AFSC resilience. This is one of the earliest studies which quantifies identified resilience enablers necessary for creating resilient AFSCs using an integrated methodology. The findings from the study will allow practitioners to anticipate risks and proactively work towards enhancing the resilience of AFSCs.

Following this introduction, the paper is organized as follows: Section 2 discusses the literature review. Through a pertinent literature review, we identify the *thirteen* enablers for enhancing resilience in the AFSCs. Section 3 highlights the integrated research methodology, a combination of GINA and FLQOWA. Section 4 presents the analysis and discussion of the results. Section 5 represents the theoretical and managerial implications. The paper concludes by underlining conclusions, limitations, and future research directions in Section 6.

2. Review of literature

This research intends to identify the enablers for creating resilient AFSCs; pertinent literature sources were analyzed (Tranfield et al., 2003). The enablers were identified through a systematic literature review. The theoretical background and the underpinning research methodology are presented in the following subsections.

2.1. Literature methodology

This study adopts a two-phased research methodology. In the first phase, the researchers identify the critical research gaps and establish the protocol for the needs of the study. Then, the scope of the study is charted, which helps frame precise RQs. Once the study scope and research objectives are established, search strings are developed to identify pertinent literature for the review. A systematic review of the literature helps provide critical insights for exploring research in emergent fields and helps frame future research directions (Samad et al., 2022; Sharma et al., 2020a). The literature review flowchart is depicted in Fig. 1.

We identified topical literature trends by deploying keyword maps. Using keywords (both generic and relevant research terms) led to various results clustered using VOSviewer, a data analytics software. This highlighted the specific keywords that were used by most of the literature and provided the timeline when the keywords were introduced (Bechtsis et al., 2022). We then referred to previous studies to include appropriate keywords in our literature search. The finalized query was:

("agricultural supply chain") OR ("agri-food supply chain") OR ("food supply chain") AND ("resilience") OR ("risk") OR ("disruption") AND ("industry4.0") OR ("artificial intelligence") OR ("additive manufacturing") OR ("augmented reality") OR ("blockchain") OR ("big data") OR ("machine learning") OR ("cloud computing") OR ("data analytics") OR ("internet of things") OR ("simulation") OR ("virtual reality") OR ("data-driven") OR ("digital twins") OR ("cyber-physical systems") OR ("robotics").

The article search was carried out using Scopus and Web of Science electronic databases. Several exclusion and inclusion criteria were applied for finalizing the pool of research articles appropriate to the present study's scope. Only peer-reviewed journal articles were considered for the present study (Sharma et al., 2020a). The other criteria for article selection are English language and articles and reviews published in the following subject categories: Business, Management and Accounting, Engineering, Computer Science, Agricultural and Biological Sciences, Social Sciences, Environmental Science, and Decision Sciences. This review did not include non-academic journal articles, conference articles, white papers, book chapters, and books. The present study also used the PRISMA (Preferred Reporting Items for Systematic Review and Meta-Analysis) technique (Moher et al., 2009). Finally, 59 articles were included in the review, and based on the thorough reading of these articles, we investigated the enablers for resilient AFSCs.

Fig. 2 highlights the keyword map from the selected articles. From the figure, a considerable amount of research is focusing on I4Ts and food supply chains nowadays. Sustainability and risk management are emergent themes in combination with AI and BCT. All the I4Ts are connected through IoT with keywords such as decision-making, decision

[2] https://wits.worldbank.org/CountryProfile/en/Country/ARE/Year/LTST/TradeFlow/Import/Partner/by-country/Product/16–24_FoodProd

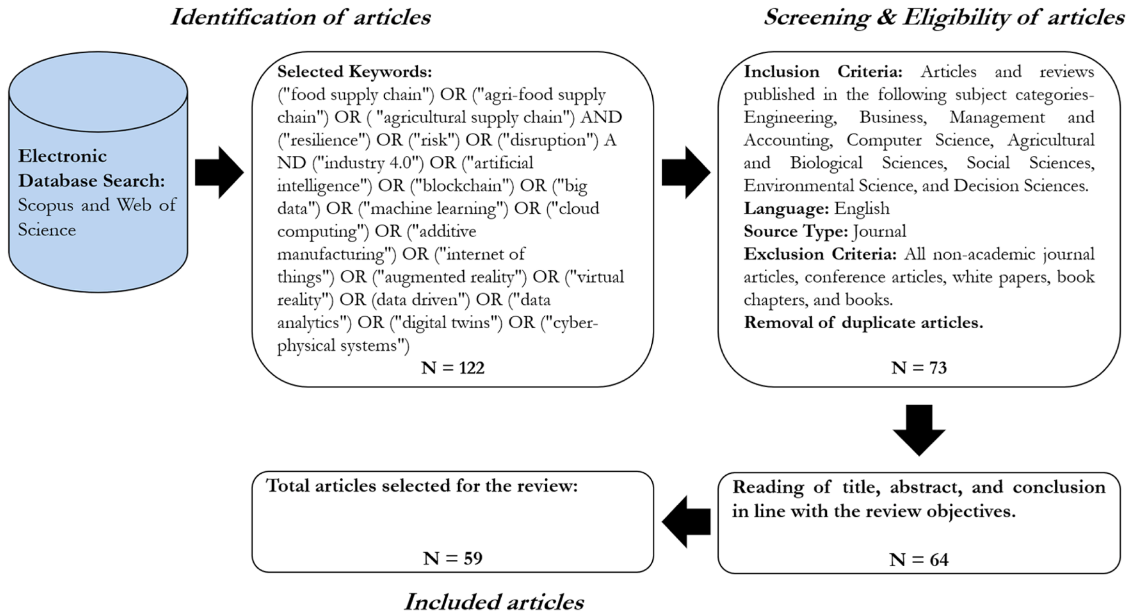

Fig. 1. Literature review flowchart.

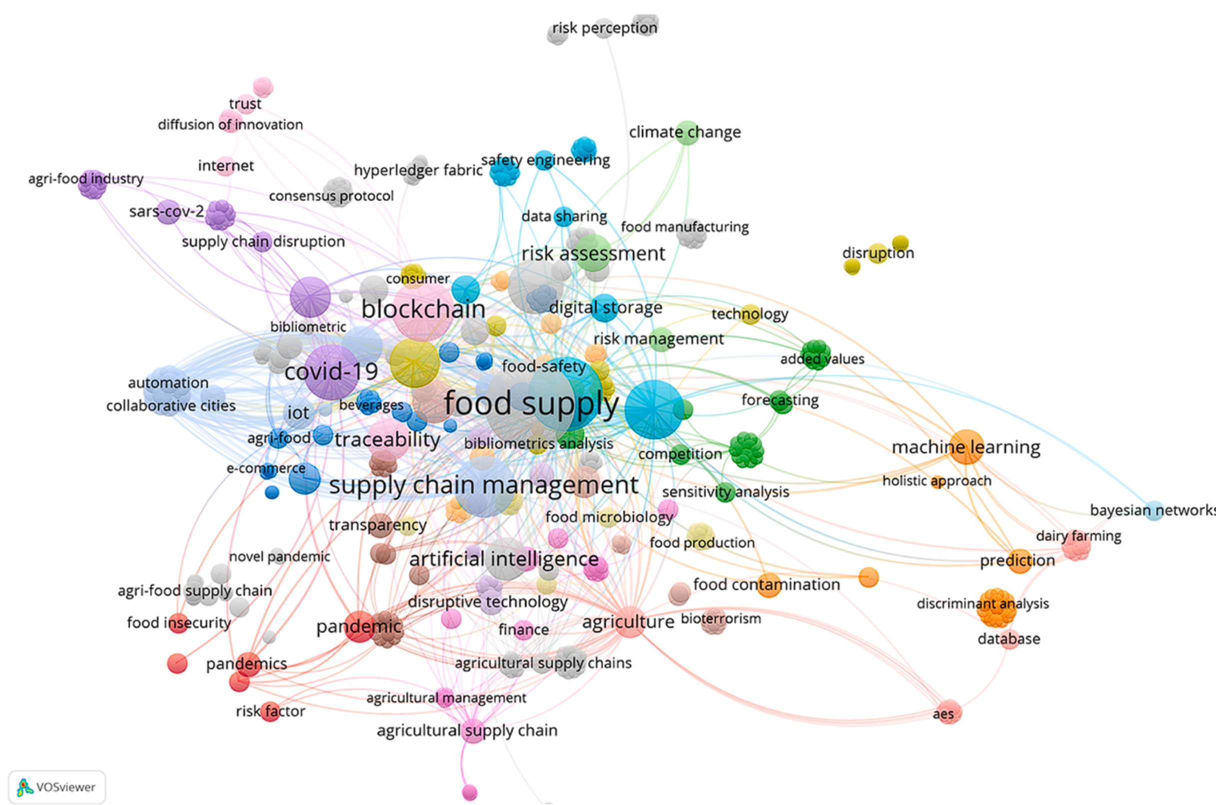

Fig. 2. Keyword map.

support systems, traceability, and sustainability. Therefore, this further strengthens our case for establishing a decision support system highlighting the enablers for creating resilient AFSCs.

Table 1 presents a summary of studies conducted in the domain of I4Ts, resilience, and supply chain management. While most of the studies have enriched the literature on critical aspects of I4Ts, resilience, and supply chain management, a few studies have observed the causal relationships among resilient enablers. Moreover, as AFSCs are critical in the UAE and the MENA region, there is a dearth of decision-making frameworks that can help practitioners better understand the factors that will help create resilient AFSCs.

Table 1
Previous studies on I4Ts, supply chain management, and supply chain resilience.

Ref.	Study type	Objective(s)	Key observation(s)
Qader et al. (2022)	Empirical	To investigate the influence of Industry 4.0 on supply chain performance.	Industry 4.0 is an enabler of supply chain resilience and improves supply chain visibility.
Oliveira-Dias et al. (2022)	Review	To investigate the linkages between industry 4.0 technologies and agile supply chains.	The study highlighted that industry 4.0 technologies and agile supply chains can enhance resilience.
Marcucci et al. (2022)	Empirical	To investigate the impact of industry 4.0 technologies on organizational resilience.	The study highlighted that the implementation of Industry 4.0 technologies enhanced organizational resilience and supply chain performance.
Ambrogio et al. (2022)	Case Study	To investigate disruption as a technological innovation for resilient manufacturing systems.	Using a case study approach, the study highlighted how disruption acts as a technological innovation platform for fostering digital sourcing and product and process innovation, thereby enhancing the resilience of the workforce and manufacturing systems.
Spieske and Birkel (2021)	Review	To investigate the relationship between Industry 4.0 and supply chain resilience.	The study reviewed 62 articles and provided a theoretical framework on the relationship between resilience and Industry 4.0 technologies.
Ivanov and Dolgui (2021)	Review	To investigate the link between risks and resilience in the Industry 4.0 paradigm.	The study proposes digital twins as a probable solution for mitigating disruption risks and enhancing supply chain resilience in Industry 4.0.
Mubarik et al. (2021)	Empirical	To investigate the impact of industry 4.0 driven supply chain on and resilience.	The study highlighted that supply chain visibility mediates the relationship between an industry 4.0-driven supply chain and resilience.
Tortorella et al. (2022)	Review	To explore the link between Industry 4.0 integration in supply chains for enhancing resilience enablers.	The study highlighted that Industry 4.0 is an enabler against disruptions, increasing supply chain resilience.

2.2. I4Ts and supply chain resilience

Since its origination in 2011,[3] industry 4.0 (I4) has brought a paradigm shift in the manufacturing sector. I4 provides a digital manufacturing ecosystem in which various production processes and technologies are integrated (horizontal and vertical integration) via the internet of things (IoT) platform, giving rise to the concept of *smart factories.* The main objectives of I4 are to improve the responsiveness and overall efficiency of the manufacturing systems. I4 is driven by real-time information exchange between different production and manufacturing value chain entities. Significant I4-enabling digital technologies along the entire supply chain are additive manufacturing (AM), Artificial Intelligence (AI), Augmented Reality (AR)/ Virtual Reality (VR), Big Data Analytics (BDA), Blockchain Technology (BCT), Cloud Computing (CC), Cyber-Physical Production Systems (CPPS), Digital Twins (DT), IoT, robotics, and simulation (Bai et al., 2022; Sharma et al., 2022a; Zheng et al., 2021). Apart from the manufacturing sector, I4 technologies' (I4T) penetration into other sectors (such as agriculture, healthcare, and transportation, to name a few) has significantly improved operational efficiency and sustainability. Table 2 depicts the usage of various I4-enabling digital technologies in AFSCs and their impact on risk/ resilience.

Research in the past has highlighted that the adoption and implementation of I4Ts in supply chains can make them more resilient and sustainable (Behl et al., 2023; Dev et al., 2021; Dilyard et al., 2021; Ekinci et al., 2022; Kumar et al., 2021; Mubarik et al., 2021; Núñez-Merino et al., 2022; Qader et al., 2022; Rajesh, 2017; Saha et al., 2022; Sharma et al., 2022). Resilience is a discrete process that increases with the increase in supply chain capabilities and decreases with the

Table 2
Usage of I4Ts in AFSCs.

Enabling Industry 4.0 Technology	Applications in AFSCs	Implication for risk/ resilience
Additive Manufacturing (AM)	For designing and developing food and agricultural equipment (Sharma et al., 2022a).	Enhanced customization of tools and equipment and localized production.
Artificial Intelligence (AI)	For performing complex tasks and forecasting abilities (Sharma et al., 2022b).	Improved precision agriculture, resource optimization, and risk prediction.
Augmented Reality (AR/VR)	Simulating the data in real-time for effective visualization and risk mitigation (Jagtap et al., 2021; Rejeb et al., 2021).	Enhanced monitoring and diagnostic capabilities, opportunities for remote collaboration, and improved training support.
Big Data Analytics (BDA)	Analysis of raw data (from agricultural operations) for deriving valuable insights (Ali and Aboelmaged, 2021; Papadopoulos et al., 2022).	Dynamic decision-making, improvised resource management, and enhanced risk management.
Blockchain Technology (BCT)	For real-time tracking, traceability, and provenance of agricultural produce along the value chain (Kamble et al., 2020; Sharma et al., 2020; Kumar et al., 2022; Sharma et al., 2022).	Improved trust and collaboration, greater traceability and transparency, improved cybersecurity, and enhanced risk management.
Cloud Computing (CC)	The platform for data storage and analysis (Mustapha et al., 2021; Saurabh and Dey, 2021).	Enhanced scalability, improved visibility, opportunities for remote collaboration, and enhanced risk management.
Cyber-Physical Production Systems (CPPS)	One of the key technologies to achieve precision agriculture (Sharma and Parhi, 2017)	Improvised automation capabilities, data-driven dynamic decision-making, and real-time monitoring capabilities.
Digital Twins (DT)	For enhancing the risk mitigation capabilities in the AFSCs (Purcell and Neubauer, 2022; Pylianidis et al., 2021).	Improved decision-making capabilities through simulation, proactive risk management, and enhanced visibility.
Internet of Things (IoT)	Helps in system connectivity through the sensors network and as a platform for hosting other I4 technologies (Sharma et al., 2022a).	Improved tracking and traceability, enhanced real-time monitoring, and precision agriculture.
Robotics and Simulation (RS)	For enhancing the operational efficiency in AFSCs (Sharma et al., 2022a).	Enhanced stress testing for improved resilience capabilities, precision agriculture, and data-driven decision-making capabilities.

[3] https://www-live.dfki.de/fileadmin/user_upload/DFKI/Medien/News_Media/Presse/Presse-Highlights/vdinach2011a13-ind4.0-Internet-Dinge.pdf

vulnerabilities. As reported by Spieske and Birkel (2021), I4Ts directly do not influence supply chain resilience but act on specific resilience enablers that act as mediating factors. Therefore, based on the systematic review, we found *thirteen* enablers for creating resilient AFSCs. The following subsection discusses these *thirteen* enablers.

2.3. AFSC resilience enablers

Resilience is a capacity of the supply chains that facilitates supply chains to achieve an uninterrupted flow of products and services during disruptions. This capacity can also be referred to as principles/ enablers that allows supply chains to achieve resilience (Rajesh, 2020). Extant literature about supply chain resilience has discussed numerous drivers and enablers across various supply chain domains (Bechtsis et al., 2022; Hosseini et al., 2019; Ralston and Blackhurst, 2020; Sharma et al., 2022b; Shishodia et al., 2023, 2022, 2019; Spieske and Birkel, 2021). The present study provides a detailed description of the enablers for achieving resilient AFSCs through I4 enabling technologies. Based on the findings from the literature review, the present study proposes thirteen enablers for achieving resiliency in the AFSCs. The thirteen enablers have been categorized into four major groups: supply chain visibility and transparency, supply chain reengineering, supply chain collaboration, and supply chain risk management culture based on the existing literature (see Table 3).

2.4. Research gaps

As the UAE is a net food-importing country, the resiliency and sustainability of its AFSCs are crucial. In the wake of recent supply chain disruptions such as COVID-19 and the geopolitical tensions between Ukraine and Russia, the AFSC organizations and the Government are doing their best to improve resilience enablers of the AFSCs (Manikas et al., 2022). There are many investment projects in the technology and the associated infrastructure for achieving the resiliency and sustainability goals (Govind et al., 2021). It has been observed that there are minimal studies that have identified the relationship between resilience enablers and have mapped them with Industry 4.0 in the case of AFSCs. Therefore, using an integrated research methodology, this study

Table 3
Resilient AFSC enablers and supporting I4Ts.

Major enablers	Sub-enablers	Description	Supporting I4Ts	Resilience characteristic exhibited	Ref.
Supply Chain Visibility and Transparency	Real-time information sharing and synchronization of product flows **(RTIS)**	Facilitates data gathering, analysis, and interpretation	IoT, CPPS, BDA, CC, BCT	Efficient transportation, supply, and demand planning, reduced operations costs, increased flexibility in operations, and increased responsiveness	Cao et al. (2022), Liu et al. (2022), Pandey et al. (2022), Le et al., (2019), (Balzarova et al., 2022; Friedman and Ormiston, 2022; Paul et al., 2021)
	Enhanced Product traceability **(EPT)**	Supports effective data connectivity throughout the AFSC	BCT, IoT, CC	Increased visibility, responsiveness, and transparency and reduced wastage	(Hazrati et al., 2022; Latino et al., 2022; Yu et al., 2019; Ali et al., 2021)
	Improved risk management of products (in transit/stocked) **(IRM)**	Achieving risk knowledge, thereby improvising risk mitigation strategies	IoT, BDA, DT, AI, AR/VR, RS	Continuous learning, adaptive decision-making capabilities	Agnusdei and Coluccia (2022), Burgos and Ivanov (2021)
Supply Chain Reengineering	Planning and Network Design **(PND)**	Proactive planning and executing continuity plan during disruptions	BDA, IoT, CC, AI	Autonomous learning and decision-making, predictive capability, adaptive capability, improved risk management	Ali and Govindan (2021); Nayal et al. (2022); Yadav et al. (2021)
	Sourcing Strategies **(SS)**	Reducing supply related ambiguities, thereby reducing potential risk sources	IoT, BDA, BCT, AM	Reduced source disruption, flexible supply base, effective inventory management, increased agility, and responsiveness	Nayal et al. (2022), Talari et al. (2022), Yu et al. (2019)
	Understanding Supply Chain Structures (physical and informational) and identifying potential bottlenecks **(SCS)**	Increasing supply chain efficiency and self-managing operations thoroughly	AI, IoT, BDA, CPPS	Improved monitoring of operations, adaptive capability, efficient risk management	Agnusdei and Coluccia (2022), Iftekhar and Cui (2021), Talari et al. (2022)
Supply Chain Collaboration	Joint Continuity Planning and decision-making for risk mitigation **(JCP)**	Improving supply chain risks and enhanced economic security	BCT, IoT, BDA, CC	Enhanced security, visibility, capacity building, effective risk management	Barbosa (2021); Galanakis et al. (2021); Yadav et al. (2021)
	Mutual Trust **(MT)**	Reducing vulnerabilities and preparing strategies across the AFSC	BCT, IoT	Improved decision-making, visibility, improved risk mitigation, improved recovery capability	Aamer et al. (2021), Ali and Govindan (2021), Bumblauskas et al. (2020)
	Willingness to share information and resources **(WSIR)**	Sharing resources in challenging conditions	IoT, CC, BCT	Improved decision-making, visibility, improved collaboration, absorptive capacity	Gružauskas et al. (2019), Kumar et al. (2020)
	Holistic demand planning and forecasting **(HDPF)**	Forecasting efficiently for reducing supply-demand imbalances	AI, IoT, BDA, CC, DT	Effective recovery capability, flexibility, responsiveness, agility	Bottani et al. (2019), Kumar et al. (2020), Nayal et al. (2022)
Supply Chain Risk Management Culture	Risk awareness mindset **(RAM)**	Enhancing and developing the risk culture in an organization	AI, AR/VR, DT, BCT, IoT, RS	Absorptive capacity, flexibility, reduced costs, increased operational effectiveness	Burgos and Ivanov (2021), Latino and Menegoli (2022), Yadav et al. (2021)
	Senior management support **(SMS)**	Helps in the continuity of operations	CC, IoT	Visibility, informed decision-making, responsive capability, enhanced recovery, and effective communication.	Aamer et al. (2021), Yadav et al. (2021)
	Revaluation of the supply base **(RSB)**	Increasing responsiveness and production flexibility	AM, IoT, CC, BCT	Flexibility, responsiveness, tracking and tracing of material flow, responsiveness, agility, readiness, recovery	Ali and Govindan (2021), Cao et al. (2022), Talari et al. (2021)

identified and assessed the role of I4Ts in enhancing the resilience enablers of AFSCs in the UAE. The study's significant implications are highlighted in the following subsections.

3. Research methodology

For realizing the research objectives, in phase 1 of the study, we explored the AFSC resilience enablers and I4Ts through an extant review of literature. In phase 2, a survey (both e-survey and the survey in physical mode) was conducted wherein respondents were asked to rate the influence relations among identified enablers, which was measured on a five-point Likert scale (1 equals very low influence and 5 as very high influence). The survey was based on the guidelines provided by Forza (2002) and was conducted with respondents having sound business knowledge of AFSCs, in particular supply chain management, industry 4.0 technologies, and supply chain resilience in the food processing industry. The study considered respondents from the food processing industries in the UAE to increase the credibility of the responses. The survey was circulated among 100 respondents. We then received 37 filled responses; 7 responses were incompletely filled which were later discarded. Therefore, 30 responses were finally considered for GINA (see Appendices A3 and A4a for questionnaire and respondent profiles). We considered GINA beacause it employed large datasets as compared to other causal analysis techniques wherein 5–10 responses are typically used. Furthermore, for FLQOWA application, the data were collected from experts holding senior designations in *five* selected AFSC orgainizations (see Appendix A4b). The authors spent around 75–90 min with each expert during each discussion. Initially, the focus was on explaining the AFSC resilience enablers and then on I4Ts importance and their extent of usage. Subsequently, they were requested to rate the usage of each I4T corresponding to each resilience enabler which in turn can create resilient AFSCs.

This study utilizes an integrated research methodology using GINA and FLQOWA. The GINA technique is used to analyze resilience enablers for AFSC, and FLQOWA is used to assess I4Ts corresponding to identified enablers (see Fig. 3). Studies in the past have also quantified resilience in the case of agricultural supply chains. For instance, the empirical study by Qader et al. (2022) highlights that Industry 4.0 is an enabler of supply chain resilience, and supply chain visibility moderated the relationship between the above two variables. The study by Ali et al. (2021) explored the relationship between various supply chain risks and Industry 4.0 in the Australian food processing sector and revealed that Industry 4.0 technologies can help mitigate disruptions by minimizing the impact of the risks on firm performance.

Similarly, the study by Sharma et al. (2022) highlighted how various industry 4.0 technology capabilities can enhance sustainable agricultural supply chain performance in the agribusiness industries in India. The case study by Brookbanks and Parry (2024) highlights how industry 4.0 technology helps build capabilities such as adaptability, improved trust, collaboration, and integration that enhance resilience in established cross-border supply chains. In conclusion, research demonstrates the significant impact of I4Ts on enhancing supply chain resilience and performance in various sectors and geographic locations, emphasizing the importance of leveraging these technologies to mitigate risks and improve overall operational efficiency.

The following subsections highlight the steps involved in the GINA technique.

3.1. Calculating resilience scores for enablers

The resilience enablers were analyzed using the GINA technique. This section describes the steps followed in the GINA technique (Rajesh,

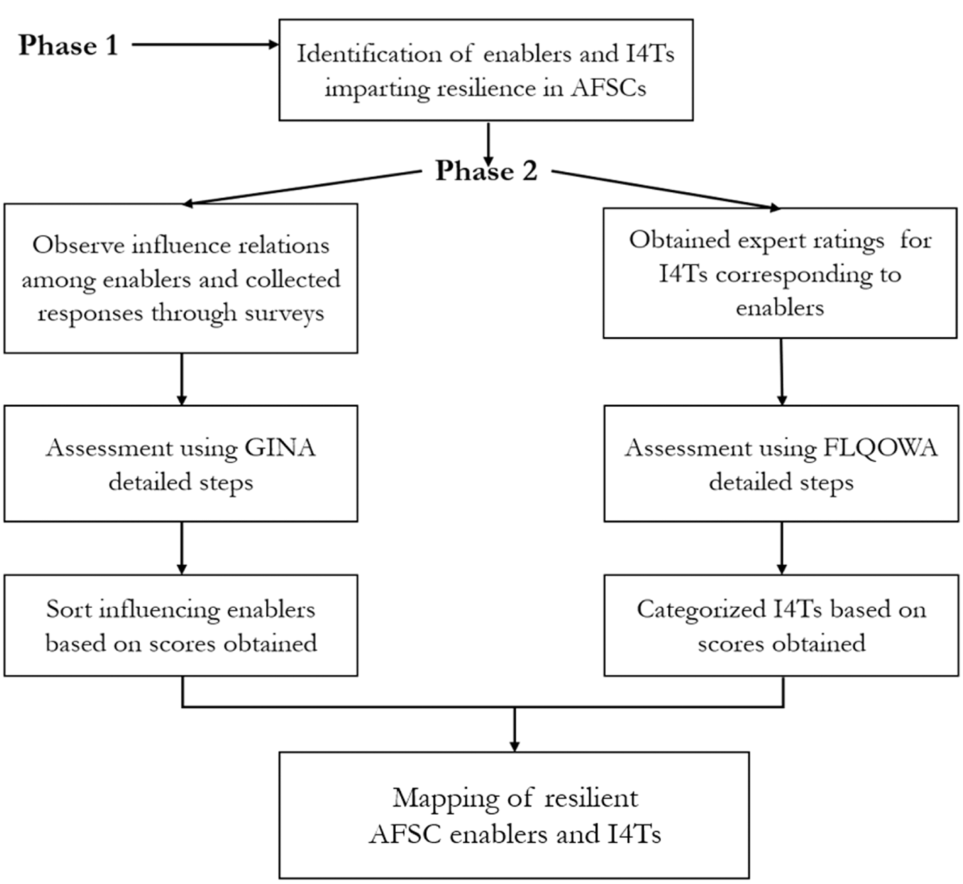

Fig. 3. Framework for the research methodology.

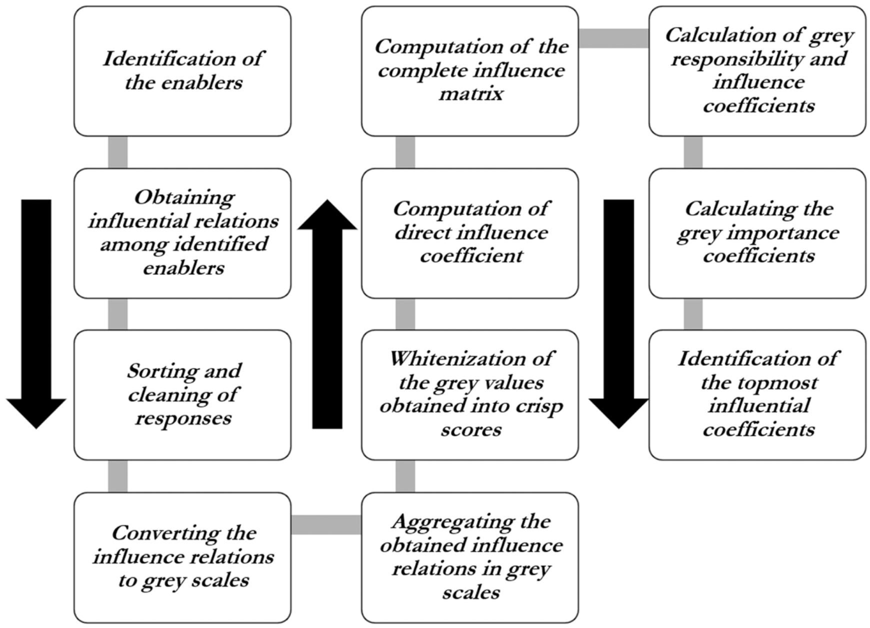

Fig. 4. GINA technique, adapted from Rajesh (2023).

2023). Fig. 4 highlights the GINA technique's flowchart. Table 4 depicts the notations used in the implemented methodology.

Step 1: **identification of the enablers**

The first step in the GINA technique is identifying and sorting relevant enablers for improving resiliency in the AFSCs. The enablers can be investigated through various methods, such as literature reviews, Delphi surveys, expert opinions, and a combination of various methods.

Step 2: **obtaining influential relations among identified enablers**

In this step, responses can be obtained through surveys or expert-based studies. The present study utilizes survey-based methods for data collection from the respondents. Then, the respondents were asked to rate the influence of one enabler over the other using a linguistic scale varying from very low to very high (1: very low and 5: very high influence). Here, a five-point Likert scale is used for recording the direct influences.

Step 3: sorting and cleaning of responses

The collected influence responses were cleaned to remove incomplete and biased responses. This process can be carried out manually or using software. Here, it is done manually by carefully observing the responses.

Step 4: **converting into grey scales**

The recorded influence relations are then converted from linguistic terms to the grey scale. The linguistic terms are converted into linguistic ratings using a linguistic interval scale, as presented in Table 5. Here, $\otimes e_{ij}$ represents the influence of enabler i over enabler j. Typically, a grey number $\otimes e_{ij}$, $\underline{\otimes} e_{ij}$ lower bound value and $\overline{\otimes} e_{ij}$ upper bound value then

Table 4
Notations used in the implemented methodology.

Notation	Description	Notation	Description
i, j	Number of enablers	$\otimes h_{ij}$	DIC
K	Number of crisp scores	$\otimes$ H	DIC matrix
$\otimes e_{ij}$	Influence of i^{th} factor over j^{th} factor	$\otimes$ N	CIC matrix
$\otimes e_j$	Sum of influence imparted by factor j in the system	$\otimes l_i$	GRC of the i^{th} factor
$\underline{\otimes} e_{ij}$	Lower bound value of the $\otimes e_{ij}$	$\otimes m_j$	GRC of the j^{th} factor
$\overline{\otimes} e_{ij}$	Upper bound value of the $\otimes e_{ij}$	t^k_{ij}	GIC

Where DIC- direct influence coefficient; CIC- complete influence coefficient; GRC- grey responsibility coefficient; GIC- grey importance coefficient

Table 5
Linguistic interval scale (adopted from Singh et al. (2022)).

Linguistic Term	Associated grey number
Very Low (VL)	[0,3]
Low (L)	[2,5]
Medium (M)	[4,7]
High (H)	[6,9]
Very High (VH)	[8,10]

$\otimes e_{ij}$ can be represented as follows:

$$\otimes e_{ij} = \left(\underline{\otimes} e_{ij}, \overline{\otimes} e_{ij}\right)$$

Step 5: aggregating the influence relations

The responses collected via the survey method are aggregated based on the guidelines proposed by Deng (1989) using the grey addition operator. This leads to the cumulative influence relation matrix. The aggregated influence can be obtained for all valid responses (n) using Equation (1) as follows:

$$\sum_{r=1}^{n} \otimes^{r}_{e_{ij}} = \left(\sum_{r=1}^{n} \underline{\otimes}^{r}_{e_{ij}}, \sum_{r=1}^{n} \overline{\otimes}_{e_{ij}}{}^{r}\right) \tag{E1}$$

Where, r = 1,2,3….n

Step 6: whitenization of obtained grey values

This step involves the whitenization of the aggregated grey influence scores into crisp scores. It can be computed using three models viz., critical (lower bound), ideal (upper bound), and typical (average) values of the aggregated influences. These are then considered for converting grey values into crisp scores.

Step 7: computing DIC matrix

The DIC is calculated using Equation (2). In this study, we have considered three crisp values viz., $k = 1, 2, 3$, which correspond to the DICs. Here, the first value is related to the critical model, the second is related to the ideal model, and the third is related to the typical model whitenization respectively,

$$\otimes h^{k}_{ij} = \frac{e^{k}_{ij}}{e^{k}_{j}}$$

Where, $i = 1,2,3\ldots n$; $j = 1,2,3\ldots n$; $k = 1,2,3$

$$H^k = \left[\otimes h_{ij}^k\right]_{n*n} = \begin{bmatrix} h_{11}^k & \cdots & h_{1n}^k \\ \vdots & \ddots & \vdots \\ h_{n1}^k & \cdots & h_{nn}^k \end{bmatrix} \tag{E2}$$

Step 8: obtaining the CIC matrix

The CIC matrix can be computed using Equation (3), as shown below.

$$N^k = \left(\left(1 - H^K\right)^{-1} - I\right) \tag{E3}$$

Where I represent the identity matrix in the same dimensions of H^k.

Similarly, the matrices of N^k can be represented as follows:

$$N^k = \left[\otimes n_{ij}^k\right]_{n*n} = \begin{bmatrix} n_{11}^k & \cdots & n_{1n}^k \\ \vdots & \ddots & \vdots \\ n_{n1}^k & \cdots & n_{nn}^k \end{bmatrix}; k = 1,2,3 \tag{E4}$$

Step 9: calculation of GRC and influence coefficients

The GRC of the i^{th} enabler and j^{th} enabler can be obtained using Equation (5) and Equation (6), respectively.

$$l_i^{k\cdot} = \frac{\left(\sum_{j=1}^{n} n_{ij}^k\right)}{\frac{1}{n}\left(\sum_{i=1}^{n}\sum_{j=1}^{n} n_{ij}^k\right)}; \tag{E5}$$

$$m_j^{k\cdot} = \frac{\left(\sum_{i=1}^{n} n_{ij}^k\right)}{\frac{1}{n}\left(\sum_{i=1}^{n}\sum_{j=1}^{n} n_{ij}^k\right)}; \tag{E6}$$

Where, $k = 1,2,3$

Step 10: calculating the GIC

The GIC can be computed using Equation (7).

$$t_{ij}^k = l_i^k + m_j^k \quad \forall i = j; k = 1,2,3 \tag{E7}$$

Step 11: identification and analysis of the topmost influential enablers

Based on the values of t_{ij}^k, the most influential enablers corresponding to critical, ideal, and most typical models can be identified. The aggregate of the values of t_{ij}^k can be obtained using Equation (8). Using the 80–20 rule, the most influential enablers will be those 20 percent having the highest significance in the system.

$$t_{ij}^k = \frac{t_{ij}^1 + 4 * t_{ij}^2 + t_{ij}^3}{u} \tag{E8}$$

Where u is an arbitrary number (often 1, 2….6)

3.2. Computing resilience scores of I4Ts

After the experts rated the identified resilience enablers, they were then asked to rate the I4Ts. The purpose of rating I4Ts is to identify the I4T that will help increase the identified enabler's resilience capability. The FLQOWA technique is used to assess I4Ts**,** which can enhance the resilience of AFSCs. It is a multicriteria decision-making methodology that combines elements of fuzzy logic, linguistic variables, and ordered weighted aggregation (OWA) to facilitate decision-making processes in uncertain, ambiguous, and subjective situations (Shishodia et al., 2019). FLQOWA finds its applications in various domains such as supplier assessment, risk assessment, finance, and engineering, where it helps decision-makers handle imprecise information and make well-informed choices.

The FLQOWA technique involves the following steps (Shishodia et al., 2019; Sharma et al., 2020b):

Step I: Fuzzy Linguistic Labelling- Decision-makers evaluate criteria or alternatives using linguistic variables.

Step II: Linguistic Quantification- Linguistic quantifiers are applied to the linguistic labels, indicating the degree of importance or significance associated with each label.

Step III: Fuzzy Aggregation- Fuzzy logic operators aggregate linguistic quantified variables for each criterion.

Step IV: Ordered Weighted Aggregation- The OWA operator is applied to the aggregated linguistic variables to obtain an overall decision or ranking.

The detailed steps for the computation of resilience scores are provided in Appendix A1.

4. Result analysis

4.1. Analysis of resilience enablers

This section focuses on the results analyzed based on the resilience scores of the enablers obtained using GINA and assessment of I4Ts using FLQOWA. The adopted GINA technique also helped prevent data losses during aggregation operations, which is prevalent in causal analysis studies such as ISM or DEMATEL. Also, the GINA technique can handle ambiguity compared to ISM, DEMATEL, and TISM (Rajesh, 2024). The comparison of GINA with other MCDM techniques is depicted as well in Appendix A2. The numerical illustration of the proposed methodology is given below:

Steps 1–6: The stepwise implementation is carried out, i.e., responses were collected, sorted, cleaned, and then converted into grey scales as depicted in Table 5. The responses were aggregated using equations (3) and (4). Further, whitenized values of aggregated responses in grey scales were computed for critical, ideal, and typical models, as shown in Table 6.

Fig. 5 depicts the influence relations of the identified enablers. The most typical values of the aggregated responses for influencing enablers highlight the level of influence among each enabler. The cumulative scores are highlighted on the outer ring, indicating the enablers' total influencing power. The outer ring highlights the overall driving power of the enablers. It indicates an enabler's significance in influencing the system.

Step 7: The direct influence coefficient matrices are shown in Table 7.

Step 8: The computed complete influence coefficients and the matrices are shown in Table 8.

Steps 9–11: The Total Influence Coefficients (TIC) are calculated using Eq. (5) to (8), and the value of $l = 1$ is used in the present study for obtaining the overall TICs, as per the GINA analysis. Using the Pareto 80–20 principle, the top 20 % of the enablers are assumed to have major influence and can act as significant enablers of Industry 4.0 that foster resilient AFSCs in UAE. It has been found that there are two major enablers with high influence coefficients and are significant enablers of Industry 4.0. These enablers are RTIS, occupying the first position, followed by EPT in the second, IRM in the third, and PND in the fourth position. Table 8 indicates the grey responsibility coefficients (GRC) of three models and the total influence of scores of the thirteen enablers considered for the present study and these responsibility coefficients are graphically represented in Fig. 6. The complete coefficient matrices are represented in Table 9.

4.2. Assessment of I4Ts

Based on the scores obtained, mapping is carried out between resilient AFSC enablers and I4Ts as shown in Table 10. The different colors are used for better visualization of the extent of usage/adoption of I4Ts in AFSCs. Specifically, the red color depicts low usage, yellow indicates medium usage, and green represents extensive usage of a particular I4T

Table 6
Critical whitenized values, ideal whitenized values, and typical whitenized values.

Critical	1	2	3	4	5	6	7	8	9	10	11	12	13	
	RTIS	**EPT**	**IRM**	**PND**	**SS**	**SCS**	**JCP**	**MT**	**WSIR**	**HDPF**	**RAM**	**SMS**	**RSB**	**Sum**
RTIS	30	115	88	128	227	223	203	54	79	77	179	101	138	1642
EPT	55	30	45	44	150	106	172	223	66	235	87	50	231	1494
IRM	78	70	30	136	225	187	85	83	207	181	62	40	82	1466
PND	235	234	230	30	160	44	78	40	132	231	115	137	55	1721
SS	62	159	57	168	30	205	77	47	96	107	121	32	176	1337
SCS	67	78	35	237	151	30	144	37	38	111	220	204	187	1539
JCP	229	156	125	177	235	88	30	220	146	102	175	174	237	2094
MT	227	195	75	110	204	87	168	30	149	165	117	102	185	1814
WSIR	146	100	185	84	124	190	179	193	30	222	208	31	63	1755
HDPF	143	58	216	201	46	78	169	79	49	30	143	109	144	1465
RAM	62	76	82	198	138	98	95	152	134	156	30	226	113	1560
SMS	146	47	43	126	152	111	78	103	34	156	221	30	155	1402
RSB	144	210	176	54	119	45	213	233	122	52	40	190	30	1628
Sum	1624	1528	1387	1693	1961	1492	1691	1494	1282	1825	1718	1426	1796	
Ideal	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	
	RTIS	**EPT**	**IRM**	**PND**	**SS**	**SCS**	**JCP**	**MT**	**WSIR**	**HDPF**	**RAM**	**SMS**	**RSB**	**Sum**
RTIS	90	437	424	355	482	379	416	474	428	445	415	536	412	5293
EPT	116	90	486	407	439	380	437	447	445	353	381	432	352	4765
IRM	166	206	90	403	429	435	445	416	362	317	386	417	446	4518
PND	225	206	282	90	443	416	461	476	387	402	414	427	339	4568
SS	207	241	140	259	90	434	450	490	472	358	387	421	401	4350
SCS	117	197	274	154	268	90	450	456	430	411	407	493	455	4202
JCP	207	279	155	113	90	266	90	431	420	395	443	379	404	3672
MT	269	268	246	203	163	94	191	90	407	415	416	443	449	3654
WSIR	224	191	235	214	206	235	140	281	90	491	471	414	380	3572
HDPF	266	243	150	238	129	194	139	97	169	90	463	380	411	2969
RAM	141	200	105	159	235	157	134	92	150	111	90	419	388	2381
SMS	283	218	127	254	114	258	170	221	248	149	157	90	502	2791
RSB	127	129	127	112	227	150	297	170	179	104	228	119	90	2059
Sum	2438	2905	2841	2961	3315	3488	3820	4141	4187	4041	4658	4970	5029	
Typical	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	
	RTIS	**EPT**	**IRM**	**PND**	**SS**	**SCS**	**JCP**	**MT**	**WSIR**	**HDPF**	**RAM**	**SMS**	**RSB**	**Sum**
RTIS	60	276	256	241.5	354.5	301	309.5	264	253.5	261	297	318.5	275	3467.5
EPT	85.5	60	265.5	225.5	294.5	243	304.5	335	255.5	294	234	241	291.5	3129.5
IRM	122	138	60	269.5	327	311	265	249.5	284.5	249	224	228.5	264	2992
PND	230	220	256	60	301.5	230	269.5	258	259.5	316.5	264.5	282	197	3144.5
SS	134.5	200	98.5	213.5	60	319.5	263.5	268.5	284	232.5	254	226.5	288.5	2843.5
SCS	92	137.5	154.5	195.5	209.5	60	297	246.5	234	261	313.5	348.5	321	2870.5
JCP	218	217.5	140	145	162.5	177	60	325.5	283	248.5	309	276.5	320.5	2883
MT	248	231.5	160.5	156.5	183.5	90.5	179.5	60	278	290	266.5	272.5	317	2734
WSIR	185	145.5	210	149	165	212.5	159.5	237	60	356.5	339.5	222.5	221.5	2663.5
HDPF	204.5	150.5	183	219.5	87.5	136	154	88	109	60	303	244.5	277.5	2217
RAM	101.5	138	93.5	178.5	186.5	127.5	114.5	122	142	133.5	60	322.5	250.5	1970.5
SMS	214.5	132.5	85	190	133	184.5	124	162	141	152.5	189	60	328.5	2096.5
RSB	135.5	169.5	151.5	83	173	97.5	255	201.5	150.5	78	134	154.5	60	1843.5
Sum	2031	2216.5	2114	2327	2638	2490	2755.5	2817.5	2734.5	2933	3188	3198	3412.5	

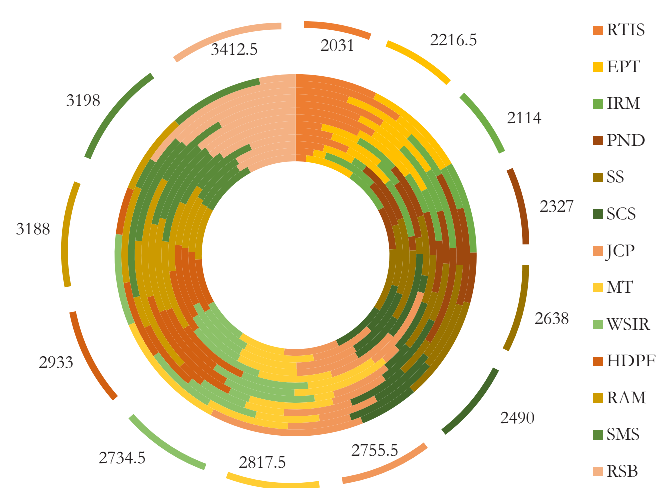

Fig. 5. Graphical outlay of influence relations among enablers.

for enhancing resilience enablers of AFSCs. The results of using FLQOWA technique highlight that AM has the highest impact on supply chain reengineering capability. Similarly, AI has the most impact on supply chain reengineering. AR and VR impact supply chain visibility and transparency and supply chain reengineering. BDA impacts almost all the resilience enablers. BCT impacts supply chain visibility and transparency, supply chain collaboration, and supply chain risk management culture. CC impacts almost all the resilience enablers. Cyber-physical production systems have a negligible impact on resilience enablers. Digital twins impact supply chain visibility and transparency and supply chain reengineering. The Internet of Things impacts almost all resilience enablers. Robotics and simulation impact supply chain visibility and transparency. It can be inferred from the results that BDA, CC, and IoT have the highest resilience scores.

5. Discussion

The present study combines different criteria for measuring the relationship between resilience enablers and how various I4Ts can significantly enhance them. It has been observed from the analysis of DIC, CIC, and GRC that the four topmost influential enablers for resilient AFSCs are supply chain visibility and transparency (RTIS, EPT, IRM) and

Table 7
Direct influence coefficient matrices.

Critical		RTIS	EPT	IRM	PND	SS	SCS	JCP	MT	WSIR	HDPF	RAM	SMS	RSB
1	**RTIS**	0.018	0.075	0.063	0.076	0.116	0.149	0.12	0.036	0.062	0.042	0.104	0.071	0.077
2	**EPT**	0.034	0.02	0.032	0.026	0.076	0.071	0.102	0.149	0.051	0.129	0.051	0.035	0.129
3	**IRM**	0.048	0.046	0.022	0.08	0.115	0.125	0.05	0.056	0.161	0.099	0.036	0.028	0.046
4	**PND**	0.145	0.153	0.166	0.018	0.082	0.029	0.046	0.027	0.103	0.127	0.067	0.096	0.031
5	**SS**	0.038	0.104	0.041	0.099	0.015	0.137	0.046	0.031	0.075	0.059	0.07	0.022	0.098
6	**SCS**	0.041	0.051	0.025	0.14	0.077	0.02	0.085	0.025	0.03	0.061	0.128	0.143	0.104
7	**JCP**	0.141	0.102	0.09	0.105	0.12	0.059	0.018	0.147	0.114	0.056	0.102	0.122	0.132
8	**MT**	0.14	0.128	0.054	0.065	0.104	0.058	0.099	0.02	0.116	0.09	0.068	0.072	0.103
9	**WSIR**	0.09	0.065	0.133	0.05	0.063	0.127	0.106	0.129	0.023	0.122	0.121	0.022	0.035
10	**HDPF**	0.088	0.038	0.156	0.119	0.023	0.052	0.1	0.053	0.038	0.016	0.083	0.076	0.08
11	**RAM**	0.038	0.05	0.059	0.117	0.07	0.066	0.056	0.102	0.105	0.085	0.017	0.158	0.063
12	**SMS**	0.09	0.031	0.031	0.074	0.078	0.074	0.046	0.069	0.027	0.085	0.129	0.021	0.086
13	**RSB**	0.089	0.137	0.127	0.032	0.061	0.03	0.126	0.156	0.095	0.028	0.023	0.133	0.017
Ideal		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
		RTIS	**EPT**	**IRM**	**PND**	**SS**	**SCS**	**JCP**	**MT**	**WSIR**	**HDPF**	**RAM**	**SMS**	**RSB**
1	**RTIS**	0.037	0.15	0.149	0.12	0.145	0.109	0.109	0.114	0.102	0.11	0.089	0.108	0.082
2	**EPT**	0.048	0.031	0.171	0.137	0.132	0.109	0.114	0.108	0.106	0.087	0.082	0.087	0.07
3	**IRM**	0.068	0.071	0.032	0.136	0.129	0.125	0.116	0.1	0.086	0.078	0.083	0.084	0.089
4	**PND**	0.092	0.071	0.099	0.03	0.134	0.119	0.121	0.115	0.092	0.099	0.089	0.086	0.067
5	**SS**	0.085	0.083	0.049	0.087	0.027	0.124	0.118	0.118	0.113	0.089	0.083	0.085	0.08
6	**SCS**	0.048	0.068	0.096	0.052	0.081	0.026	0.118	0.11	0.103	0.102	0.087	0.099	0.09
7	**JCP**	0.085	0.096	0.055	0.038	0.027	0.076	0.024	0.104	0.1	0.098	0.095	0.076	0.08
8	**MT**	0.11	0.092	0.087	0.069	0.049	0.027	0.05	0.022	0.097	0.103	0.089	0.089	0.089
9	**WSIR**	0.092	0.066	0.083	0.072	0.062	0.067	0.037	0.068	0.021	0.122	0.101	0.083	0.076
10	**HDPF**	0.109	0.084	0.053	0.08	0.039	0.056	0.036	0.023	0.04	0.022	0.099	0.076	0.082
11	**RAM**	0.058	0.069	0.037	0.054	0.071	0.045	0.035	0.022	0.036	0.027	0.019	0.084	0.077
12	**SMS**	0.116	0.075	0.045	0.086	0.034	0.074	0.045	0.053	0.059	0.037	0.034	0.018	0.1
13	**RSB**	0.052	0.044	0.045	0.038	0.068	0.043	0.078	0.041	0.043	0.026	0.049	0.024	0.018
Typical		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
		RTIS	**EPT**	**IRM**	**PND**	**SS**	**SCS**	**JCP**	**MT**	**WSIR**	**HDPF**	**RAM**	**SMS**	**RSB**
1	**RTIS**	0.03	0.125	0.121	0.104	0.134	0.121	0.112	0.094	0.093	0.089	0.093	0.1	0.081
2	**EPT**	0.042	0.027	0.126	0.097	0.112	0.098	0.111	0.119	0.093	0.1	0.073	0.075	0.085
3	**IRM**	0.06	0.062	0.028	0.116	0.124	0.125	0.096	0.089	0.104	0.085	0.07	0.071	0.077
4	**PND**	0.113	0.099	0.121	0.026	0.114	0.092	0.098	0.092	0.095	0.108	0.083	0.088	0.058
5	**SS**	0.066	0.09	0.047	0.092	0.023	0.128	0.096	0.095	0.104	0.079	0.08	0.071	0.085
6	**SCS**	0.045	0.062	0.073	0.084	0.079	0.024	0.108	0.087	0.086	0.089	0.098	0.109	0.094
7	**JCP**	0.107	0.098	0.066	0.062	0.062	0.071	0.022	0.116	0.103	0.085	0.097	0.086	0.094
8	**MT**	0.122	0.104	0.076	0.067	0.07	0.036	0.065	0.021	0.102	0.099	0.084	0.085	0.093
9	**WSIR**	0.091	0.066	0.099	0.064	0.063	0.085	0.058	0.084	0.022	0.122	0.106	0.07	0.065
10	**HDPF**	0.101	0.068	0.087	0.094	0.033	0.055	0.056	0.031	0.04	0.02	0.095	0.076	0.081
11	**RAM**	0.05	0.062	0.044	0.077	0.071	0.051	0.042	0.043	0.052	0.046	0.019	0.101	0.073
12	**SMS**	0.106	0.06	0.04	0.082	0.05	0.074	0.045	0.057	0.052	0.052	0.059	0.019	0.096
13	**RSB**	0.067	0.076	0.072	0.036	0.066	0.039	0.093	0.072	0.055	0.027	0.042	0.048	0.018

Table 8
Grey responsibility, influence, and total influence coefficients (GRC, GIC, and TIC).

	Critical			**Ideal**			**Typical**			**Aggregate**		**Total Influence**
Sub Enablers	**GIC**	**GRC**	**Sum**	**GIC**	**GRC**	**Sum**	**GIC**	**GRC**	**Sum**	**GIC**	**GRC**	
RTIS	0.077	0.077	0.154	0.077	0.11	0.187	0.076	0.099	0.176	0.077	0.098	0.175
EPT	0.077	0.071	0.148	0.077	0.099	0.176	0.076	0.088	0.165	0.077	0.087	0.164
IRM	0.076	0.07	0.147	0.077	0.091	0.168	0.076	0.085	0.162	0.077	0.084	0.161
PND	0.077	0.081	0.158	0.0769	0.093	0.17	0.077	0.091	0.168	0.077	0.09	0.167
SS	0.077	0.064	0.141	0.0768	0.086	0.163	0.077	0.08	0.157	0.077	0.079	0.156
SCS	0.076	0.071	0.148	0.077	0.079	0.156	0.076	0.077	0.154	0.077	0.077	0.154
JCP	0.077	0.099	0.176	0.077	0.071	0.148	0.077	0.081	0.158	0.077	0.083	0.16
MT	0.077	0.086	0.163	0.0768	0.074	0.151	0.076	0.078	0.155	0.077	0.079	0.156
WSIR	0.077	0.083	0.16	0.0768	0.072	0.149	0.077	0.075	0.152	0.077	0.077	0.154
HDPF	0.076	0.072	0.148	0.077	0.062	0.139	0.077	0.065	0.142	0.077	0.066	0.143
RAM	0.076	0.075	0.152	0.0769	0.049	0.126	0.076	0.056	0.13	0.077	0.058	0.135
SMS	0.076	0.064	0.141	0.0769	0.062	0.139	0.076	0.062	0.138	0.077	0.063	0.139
RSB	0.077	0.082	0.159	0.077	0.045	0.122	0.076	0.056	0.133	0.077	0.059	0.136

supply chain reengineering (PND) in the AFSCs. Studies in the past (see Zhao et al., 2024a; Zhao et al., 2024b) have also highlighted that real-time information exchange through information and communication technology tools and supply chain collaboration leads to enhanced resilience capabilities in the AFSCs. Therefore, the findings are in line with that of the previous studies on AFSC resilience. Similarly, from the assessment of I4Ts, it has been found that IoT has a significant contribution in enhancing supply chain reengineering and supply chain management risk culture, CC in supply chain collaboration and supply chain visibility and transparency, and BDA and BCT in supply chain reengineering and supply chain visibility and transparency.

Overall, the results highlight the most widely used resilience enablers and I4Ts in AFSCs. They allow practitioners to arrive at a trade-off between various I4Ts to be adopted well in advance, depending on the

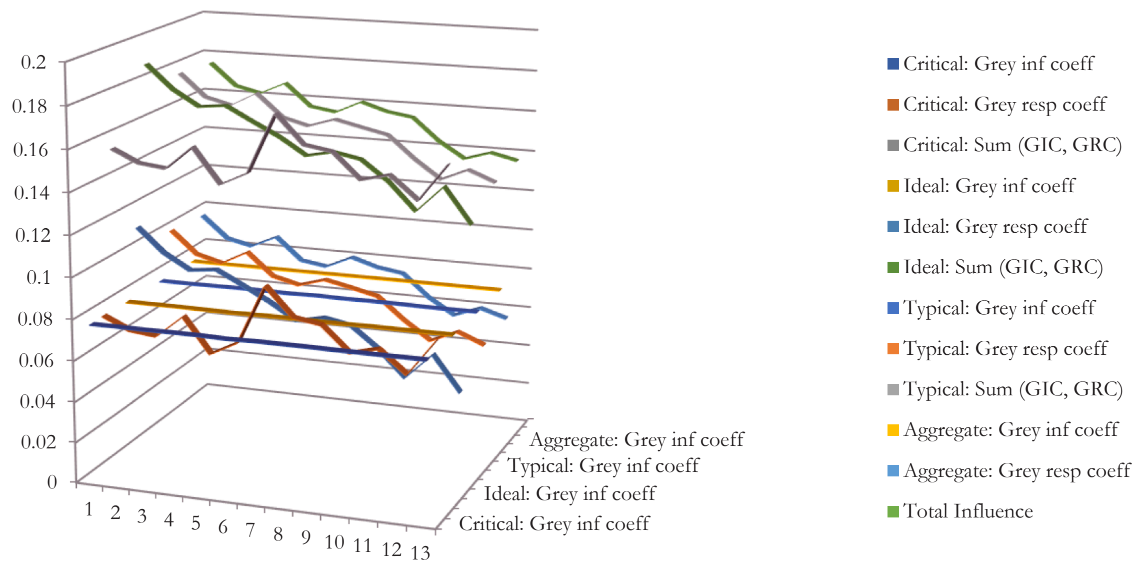

Fig. 6. Graphical representation of coefficients and total influence.

resilience requirement for different phases in the AFSCs.

5.1. Theoretical implications

The theoretical implications of the study are three-fold; firstly, the study proposes an integrated methodology (GINA and FLQOWA) that highlights the need for a comprehensive approach for evaluating AFSC resilience considering multiple factors, I4Ts, and their interactions. Secondly, there is an amalgamation of factors that were considered and assessed independently in past studies for evaluating AFSC resilience. Also, prominent I4Ts are evaluated across various AFSC enablers. Thirdly, the identified enablers were prioritized based on the resilience scores obtained, depending upon their importance, such as low, medium, and high. Furthermore, organizations can deploy I4Ts for improving AFSC resilience enablers based on the strength and weakness of each I4T. With the help of this integrated methodology, the organizations can formulate strategies for strengthening the enablers with low resilience scores.

5.2. Managerial implications

This study offers various managerial implications. Firstly, organizations can leverage resilience enablers to create a competitive advantage, as disruptions in the AFSCs have significant consequences. The I4Ts can improve end-to-end supply chain visibility in the AFSCs through enhanced real-time information sharing, improved risk management of products, enhanced product traceability, and supply chain reengineering via planning and network design. I4Ts allow procurement and risk specialists to adjust and control the AFSCs in real time. Organizations can use various software tools and platforms (such as Resilience360, RiskMethods, and GEOCOM) for data-driven proactive decision-making to improve risk planning and help create resilient AFSCs. Secondly, the data collected from various AFSC phases can be used for disruption identification. Furthermore, these data-driven analytics based on I4-driven technologies (such as digital twins) can be used in developing disruption scenarios for resilient AFSC planning and design. Thirdly, based on the resilience scores obtained, the organizations can use this information for a long-term perspective on strategic planning and investment decisions that directly or indirectly impact their AFSCs. Organizations can improve supply chain collaboration within the AFSC industry to strengthen resilience between various AFSC sectors.

The findings from the present study are in line with the study by Fatorachian and Kazemi (2021), which underlines the contributions/benefits of I4 practices in enhancing supply chain integration, providing real-time visibility, and its enabling technologies to improve transparency and flexibility, thereby leading to entire performance improvement in the supply chains. BCT, in particular, has begun revolutionizing various aspects of AFSCs, such as smart contracts between producers and consumers for improving food traceability and safety measures (Kamble et al., 2020; Sharma et al., 2021). The I4 paradigm is driven by information technology capabilities, which are now extended to cognitive-based technologies such as AI and ML-based algorithms to ensure product development growth as required.

6. Conclusions, limitations, and future research directions

The present study explored the role of I4Ts in enhancing the resilience of AFSCs. The study used an integrated approach to assess the most influential enablers of AFSCs and the usage of different I4Ts to enhance supply chain operations' resiliency. Therefore, an extant literature review was conducted to identify the enablers. Then, an advanced causal modelling GINA technique was applied to identify the most influential enablers. Subsequently, the FLQOWA technique was adopted to identify the usage of a particular I4T, which further enhances the resilience of the identified enablers based on scores obtained. FLQOWA is used to infer the resilience scores of I4Ts and then the scores were prioritized into low, medium, and high as per usage with respect to enablers. For instance, a resilience enabler is found to have a low score (means susceptibility to risk is high). The AFSC organization then needs to identify and assess the probable risks. As operations are becoming more data intensive, organizations globally are finding innovative ways of adopting and implementing I4Ts in their operations to deal with such risks and becoming resilient. Thereby the AFSC organizations can formulate resilience strategies for the enablers using I4Ts. It has been found that the topmost influential enablers in the AFSCs are RTIS, PND, IRM, and EPT. The study confirmed that the emerging I4Ts have the potential to enhance the supply chain resilience of the AFSCs and can handle uncertainty and disruptions.

The usage of the FLQOWA technique further validated this. For instance, the Internet of Things and cloud computing have been found to be extensively used to improve the resiliency of AFSC operations. There are specific implications for the managers/practitioners of the processing industries regarding adopting I4 practices and their enabling technologies. These I4Ts can potentially uplift the supply chain resilience (in all aspects of preparedness, response, and recovery), improving overall supply chain performance. Managers can use I4Ts to develop resilience,

Table 9
Complete coefficient matrices.

	1	2	3	4	5	6	7	8	9	10	11	12	13	
Critical	**RTIS**	**EPT**	**IRM**	**PND**	**SS**	**SCS**	**JCP**	**MT**	**WSIR**	**HDPF**	**RAM**	**SMS**	**RSB**	**Sum**
RTIS	232.757	232.843	232.585	232.925	232.815	232.164	232.825	232.785	232.793	232.522	232.529	232.508	232.982	3025.033
EPT	215.122	215.133	214.919	215.202	215.116	214.479	215.159	215.234	215.125	214.955	214.835	214.832	215.357	2795.468
IRM	210.666	210.69	210.456	210.795	210.691	210.095	210.646	210.675	210.761	210.481	210.376	210.363	210.808	2737.503
PND	243.897	243.932	243.703	243.895	243.81	243.061	243.789	243.803	243.859	243.622	243.503	243.521	243.969	3168.364
SS	193.972	194.061	193.803	194.117	193.918	193.463	193.962	193.976	193.999	193.779	193.74	193.707	194.164	2520.661
SCS	214.199	214.233	213.988	214.382	214.191	213.506	214.204	214.187	214.176	213.974	213.985	214.012	214.399	2783.436
JCP	298.909	298.913	298.585	299	298.842	297.916	298.762	298.922	298.874	298.495	298.465	298.486	299.105	3883.274
MT	258.307	258.329	257.993	258.35	258.233	257.442	258.247	258.21	258.274	257.971	257.892	257.897	258.456	3355.601
WSIR	252.117	252.121	251.925	252.202	252.055	251.377	252.104	252.155	252.052	251.864	251.805	251.722	252.244	3275.743
HDPF	216.124	216.101	215.99	216.246	216.032	215.423	216.103	216.092	216.078	215.813	215.82	215.823	216.257	2807.902
RAM	226.342	226.373	226.151	226.508	226.326	225.661	226.323	226.397	226.387	226.13	226.012	226.14	226.512	2941.262
SMS	194.482	194.454	194.252	194.559	194.439	193.867	194.42	194.465	194.418	194.257	194.255	194.167	194.613	2526.648
RSB	246.314	246.383	246.109	246.358	246.252	245.502	246.317	246.386	246.311	245.981	245.915	246.009	246.419	3200.256
Sum	3003.208	3003.566	3000.459	3004.539	3002.72	2993.956	3002.861	3003.287	3003.107	2999.844	2999.132	2999.187	3005.285	39021.15
Ideal	**RTIS**	**EPT**	**IRM**	**PND**	**SS**	**SCS**	**JCP**	**MT**	**WSIR**	**HDPF**	**RAM**	**SMS**	**RSB**	**Sum**
RTIS	217.149	217.283	217.502	217.06	216.882	217.265	217.482	216.851	216.827	217.236	217.019	217.03	217.217	2822.803
EPT	194.507	194.513	194.836	194.434	194.252	194.605	194.804	194.23	194.216	194.559	194.378	194.375	194.549	2528.258
IRM	180.024	180.051	180.191	179.94	179.771	180.113	180.287	179.746	179.723	180.049	179.889	179.884	180.064	2339.732
PND	183.043	183.049	183.253	182.837	182.765	183.102	183.288	182.749	182.718	183.064	182.888	182.88	183.041	2378.677
SS	170.089	170.11	170.248	169.951	169.739	170.153	170.32	169.824	169.811	170.107	169.946	169.942	170.103	2210.343
SCS	156.953	156.99	157.168	156.828	156.707	156.956	157.199	156.733	156.72	157.011	156.856	156.861	157.008	2039.99
JCP	141.189	141.219	141.324	141.034	140.893	141.203	141.295	140.957	140.948	141.21	141.081	141.059	141.201	1834.613
MT	146.968	146.973	147.115	146.818	146.665	146.921	147.087	146.628	146.691	146.97	146.826	146.821	146.965	1909.448
WSIR	142.043	142.039	142.194	141.914	141.774	142.047	142.161	141.771	141.719	142.077	141.932	141.912	142.044	1845.627
HDPF	122.82	122.818	122.914	122.702	122.556	122.801	122.906	122.531	122.539	122.747	122.709	122.686	122.811	1595.54
RAM	97.359	97.383	97.452	97.281	97.209	97.37	97.459	97.161	97.167	97.336	97.239	97.299	97.389	1265.104
SMS	122.611	122.594	122.693	122.49	122.335	122.601	122.7	122.347	122.344	122.551	122.435	122.415	122.611	1592.727
RSB	88.927	88.934	89.022	88.844	88.792	88.939	89.061	88.767	88.764	88.912	88.853	88.826	88.905	1155.546
Sum	1963.682	1963.956	1965.912	1962.133	1960.34	1964.076	1966.049	1960.295	1960.187	1963.829	1962.051	1961.99	1963.908	25518.41
Typical	**RTIS**	**EPT**	**IRM**	**PND**	**SS**	**SCS**	**JCP**	**MT**	**WSIR**	**HDPF**	**RAM**	**SMS**	**RSB**	Sum
RTIS	−517.506	−516.888	−517.363	−517.824	−517.79	−516.863	−518.323	−517.389	−517.886	−517.907	−516.918	−516.849	−517.358	−6726.86
EPT	−459.79	−459.339	−459.666	−460.088	−460.07	−459.249	−460.526	−459.675	−460.137	−460.146	−459.295	−459.238	−459.666	−5976.89
IRM	−442.899	−442.446	−442.883	−443.184	−443.171	−442.366	−443.634	−442.828	−443.238	−443.268	−442.438	−442.384	−442.801	−5757.54
PND	−477.907	−477.431	−477.846	−478.345	−478.258	−477.41	−478.747	−477.877	−478.331	−478.334	−477.446	−477.384	−477.866	−6213.18
SS	−420.291	−419.84	−420.261	−420.586	−420.645	−419.788	−420.992	−420.221	−420.617	−420.651	−419.849	−419.806	−420.194	−5463.74
SCS	−404.035	−403.611	−403.971	−404.309	−404.31	−403.63	−404.684	−403.961	−404.349	−404.359	−403.579	−403.52	−403.917	−5252.24
JCP	−423.91	−423.485	−423.899	−424.271	−424.265	−423.492	−424.725	−423.86	−424.279	−424.307	−423.488	−423.446	−423.842	−5511.27
MT	−409.687	−409.284	−409.68	−410.045	−410.036	−409.325	−410.449	−409.74	−410.058	−410.072	−409.305	−409.255	−409.637	−5326.57
WSIR	−394.228	−393.848	−394.176	−394.547	−394.545	−393.811	−394.941	−394.197	−394.632	−394.551	−393.812	−393.796	−394.177	−5125.26
HDPF	−338.093	−337.776	−338.065	−338.352	−338.4	−337.77	−338.718	−338.122	−338.439	−338.471	−337.755	−337.729	−338.048	−4395.74
RAM	−292.175	−291.867	−292.15	−292.372	−292.373	−291.861	−292.689	−292.153	−292.425	−292.441	−291.91	−291.797	−292.1	−3798.31
SMS	−322.339	−322.049	−322.361	−322.604	−322.626	−322.023	−322.95	−322.35	−322.665	−322.675	−322.054	−322.052	−322.288	−4191.04
RSB	−294.924	−294.613	−294.887	−295.175	−295.142	−294.633	−295.41	−294.886	−295.185	−295.222	−294.647	−294.606	−294.915	−3834.25
Sum	−5197.78	−5192.48	−5197.21	−5201.7	−5201.63	−5192.22	−5206.79	−5197.26	−5202.24	−5202.4	−5192.5	−5191.86	−5196.81	−67572.9

Table 10
Mapping of resilient AFSC enablers with I4Ts.

Enablers/ I4Ts	AM	AI	AR/VR	BDA	BCT	CC	CPPS	DT	IoT	RS
Supply Chain Visibility and Transparency	0.325	0.218	0.366	0.757	0.609	0.757	0.188	0.419	0.312	0.355
Supply Chain Reengineering	0.757	0.567	0.366	0.906	0.229	0.567	0.146	0.408	0.906	0.165
Supply Chain Collaboration	0.100	0.270	0.123	0.592	0.639	0.769	0.100	0.193	0.381	0.123
Supply Chain Risk Management Culture	0.146	0.206	0.165	0.515	0.609	0.567	0.101	0.188	0.906	0.146

for instance, by deploying BCT and IoT for better tracking and traceability of suppliers and products. These I4Ts will be helpful in providing real-time information, which is crucial for the interconnectedness/ integration among various supply chain entities internally and externally, thereby leading to improved supply chain performance. As the concept of '*metaverse*' in the supply chains is also catching up nowadays (Davies et al., 2024; Dolgui and Ivanov, 2023), AFSC organizations can use DT and AR/VR for efficient risk mitigation planning through simulation. The significant advantage of using I4Ts could be mapping the entire supply chain (their primary, second, and tertiary suppliers, number of warehouses and locations, logistics, and transportation services), starting from raw material procurement to the delivery of finished goods. The firms can be well prepared for unforeseen events if informed and have real-time information about the supply chain flow. It is also suggested that agri-food processing organizations can make use of a resilience dashboard wherein data from the identified enablers is obtained and tracked for long-term resilience performance. The identified enablers can be tested along other phases of the AFSCs. Organizations can implement risk mitigation practices in an unpredictable business environment. The present study also reiterates the statement for the use of I4Ts for enhancing supply chain resilience by Ivanov et al. (2021): *supply chains will be as good as the digital technologies supporting* them.

The present study has three major contributions viz., first, it identifies and quantifies critical enablers and I4Ts that impart resilience in AFSCs; second, the scores obtained helped in identifying the influential enablers and prioritization of the I4Ts associated with them; third, we developed an integrated matrix to map I4Ts and AFSC resilience enablers. This matrix can be adopted as a tool for formulating strategies to enhance resilience of AFSC organizations.

The study has certain limitations including, the enablers considered in the study have cause-and-effect relationships; therefore, future studies may check whether their factors are causal or not before implementing this methodology. Other data-cleaning techniques can be used for more reliable results. Future studies can explore different techniques, particularly in survey-based studies. Another limitation of this work is that the study was carried out in the UAE, which may hinder the generalizability of the results. Further, weight and factor ratings by AFSC practitioners may have been influenced by personal biases. Future studies can explore alternative weighting methods but also combine our assessment approach with other multi-criteria decision-making approaches to create resilient AFSCs. Although the list of identified AFSC resilience enablers is not exhaustive, future studies can utilize the identified enablers as a base and investigate further using empirical studies.

CRediT authorship contribution statement

Balan Sundarakani: Writing – review & editing, Funding acquisition. **Ioannis Manikas:** Writing – review & editing, Funding acquisition. **Rohit Sharma:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare no potential conflict of interest.

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Appendix A1: FLQOWA technique

Table A 1.1
Notations for the FLQOWA technique

Notations used	Description
i	*Number of resilient AFSC enablers*
j	*Number of supporting I4.0 technologies (I4T)*
k	*Number of experts*
$\boldsymbol{a}_{ij}^{k}$	*Expert input of 'j^th' I4T enhancing 'i^th' enabler*
$\boldsymbol{b}_{ij}^{k}$	*Normalized rating of 'j^th' I4T enhancing 'i^th' enabler*
$\boldsymbol{a}_{j}^{k^{min}}$	*Min. value of 'i^th' enabler among all 'j^th' I4T* $\{a_{1j}^{k}, a_{2j}^{k}, \ldots\ldots\ldots\ldots a_{nj}^{k}\}$
$\boldsymbol{a}_{j}^{k^{max}}$	*Max. value of 'i^th' enabler among all 'j^th' I4T* $\{a_{1j}^{k}, a_{2j}^{k}, \ldots\ldots\ldots\ldots a_{nj}^{k}\}$
$\boldsymbol{w}_{j}$	*W of 'j^th' I4T*
$\boldsymbol{w}_{j}^{*}$	*W**
ResE_{i}	*Resilience Score of an enabler (i)*

Where W = Aggregation weighted vector; W* = Maximal entropy aggregation weighted vector

Detailed steps for FLQOWA are derived from Shishodia et al. (2019) **and** Sharma et al. (2020b)**:**

Step 1: Identifying and listing the set of enablers for enhancing AFSC resilience.

Let $E_i = \{E_1, E_2, E_3, \ldots\ldots\ldots, E_m\}$ are the set of m enablers, where i = (1,2,3, …., m).

Step 2: Listing all I4.0 technologies responsible for enhancing resilience enablers in AFSCs. Let there be n independent I4.0 technologies(I4Ts) [i.e. $\{I4T_1, I4T_2, I4T_3, \ldots\ldots\ldots, I4T_n\}$, where j = (1,2, 3……, n)].

Step 3: Construct multiple enabler/ attribute matrix $A = [a_{ij}^{k}]$ comprising of non-commensurate inputs provided by the experts corresponding to each enabler.

Step 4: Converting the multiple enabler/ attribute matrix $A = [a_{ij}^{k}]$ to a fuzzy multiple enabler/ attribute matrix $B = [b_{ij}^{k}]$ using the fuzzy membership function and equations (EA 1.1) and (EA 1.2) (Zhang et al., 2003).

Conversion of linguistic terms into ratings using an interval scale as shown in Table A1.2.

Table A1.2
Linguistic interval scale

Linguistic term set	VL	L	M	H	VH
Fuzzy number	0 0 0.3	0 0.3 0.50	0.3 0.50 0.7	0.5 0.7 0.9	0.7 0.9 1
Membership degree	0 1 0	0 1 0	0 1 0	0 1 0	0 1 1

$$[\boldsymbol{b}_{ij}^{k}] = \frac{\boldsymbol{a}_{ij}^{k} - \boldsymbol{a}_{j}^{k^{min}}}{\boldsymbol{a}_{j}^{k^{max}} - \boldsymbol{a}_{j}^{k^{min}}};\textit{for the maximization attribute} \tag{EA1.1}$$

$$[\boldsymbol{b}_{ij}^{k}] = \frac{\boldsymbol{a}_{j}^{k^{max}} - \boldsymbol{a}_{ij}^{k}}{\boldsymbol{a}_{j}^{k^{max}} - \boldsymbol{a}_{j}^{k^{min}}};\textit{for the minimization attribute} \tag{EA1.2}$$

Where i = 1,……m j = 1,….,n; k = no. of experts,

$\boldsymbol{a}_{j}^{k^{max}} = \max\{a_{1j}^{k}, a_{2j}^{k}, \ldots\ldots\ldots\ldots a_{nj}^{k}\}$,

$\boldsymbol{a}_{j}^{k^{min}} = \min\{a_{1j}^{k}, a_{2j}^{k}, \ldots\ldots\ldots\ldots a_{nj}^{k}\}$

Step 5: Computation of the aggregation weighted vector W

The linguistic quantifiers usually compute the ordered weights by following a relationship described by Q which is a monotonically non-decreasing fuzzy linguistic statement. Here, weights corresponding to Q criteria "*as many as possible*" are considered which are then computed using equations (EA 1.3) and (EA 1.4) because it resembles the perception of interviewed practicing managers.

$$w_j = Q\left(\frac{j}{n}\right) - Q\left(\frac{j-1}{n}\right), j = 1, \ldots, n \tag{EA1.3}$$

$$Q(r) = \begin{cases} 0 if r < 0.5 \\ \dfrac{r - 0.5}{1 - 0.5} if 0.5 \le r \le 1, \\ 1 if r > 1 \\ r \in [0, 1] \end{cases} \quad (EA1.4)$$

NB: EA 1.4 highlights the quantifier *Q(r)* for the criteria "*as many as possible*" and *r* belongs to [0,1] (Chang et al., 2006).

Step 6: Minimization of the entropy of the FLQOWA operator

Optimization requires calculating the degree of "orness" and "entropy." Orness is computed based on the initial aggregation weighted vector W using equation (EA 1.5). Optimization is then calculated, keeping *orness* constant for obtaining the maximal entropy aggregation weighted vector W* using equations (EA 1.6), (EA 1.7), (EA 1.8), and (EA 1.9). The entropy aggregates maximum information from the objectives.

$$\text{Orness}(W) = \frac{1}{n-1}\sum_{j=1}^{n}(n-j)w_j \quad (EA1.5)$$

$$\text{Entropy}(W) = -\sum_{j=1}^{n} w_j \ln w_j \quad (EA1.6)$$

Equation (EA 1.7) is further simplified to obtain maximal entropy and is renamed as W*

Maximize

$$-\sum_{j=1}^{n} w_j \ln w_j \quad (EA1.7)$$

Subject to

Orness (W) $= \frac{1}{n-1}\sum_{j=1}^{n}(n-j)w_j$,

$$\sum_{j=1}^{n} w_j = 1,$$

$$w_j \epsilon [0, 1],$$

where j = 1,2,3,…, n.

$$\sum_{j=1}^{n}\left(\frac{n-j}{n-1} - \text{Orness}(W)\right)h^{n-j} = 0$$

$$w_j^* = \frac{h^{n-j}}{\sum_{j=1}^{n} h^{n-j}} \quad (EA1.8)$$

Where, j = 1,2,3,….,n

Step 7: Determining resilience scores of enabler(s)

The resilience score can be determined using equation (EA 1.9).

$$\text{Resilience Score : Res E} = [w_j^* * b_{ij}^k] \quad (EA1.9)$$

Sample calculation is highlighted in Table A1.3.

Table A1.3
Sample calculation

Enablers	Sub-enablers	wj*	Normalized ordered argument(bij)	Weighted score
SCC	JCP	0.031	0.9	0.0279
	MT	0.085	0.9	0.0765
	WSIR	0.235	0.9	0.2115
	HDPF	0.647	0.7	0.4529
Res E1				0.7688

Appendix A2: comparative analysis of GINA technique in comparison over other MCDM techniques

Table A 2.1 draws comparison between GINA and other MCDM techniques.

Table A 2.1
GINA vs other MCDM techniques (adapted from Rajesh, 2024)

Technique	Attribute						
	Separate Cause and Effects	Influential Causal Pairs	Handling Large Datasets	Creating Diagraphs	Creating Structural Diagrams	Creating Importance Relations	Handling Ambiguity
Interpretive Structural Modelling (ISM)	Yes	No	No	Yes	Yes	No	No
Total Interpretive Structural Modelling (TISM)	Yes	No	No	Yes	Yes	No	No
Decision Making Trial and Evaluation Laboratory (DEMATEL)	Yes	No	No	Yes	No	Yes	No
Fuzzy/ Grey DEMATEL	Yes	No	No	Yes	No	Yes	Yes
Grey Causal Modelling (GCM)	Yes	Yes	No	No	No	Yes	Yes
Grey Influence Analysis (GINA)	Yes	No	Yes	No	No	Yes	Yes

Appendix A3: respondent profile

The respondent profile is summarized in Figures A 3.1, A 3.2 and A 3.3.

Figure A 3.1. Position characteristics of the respondents.

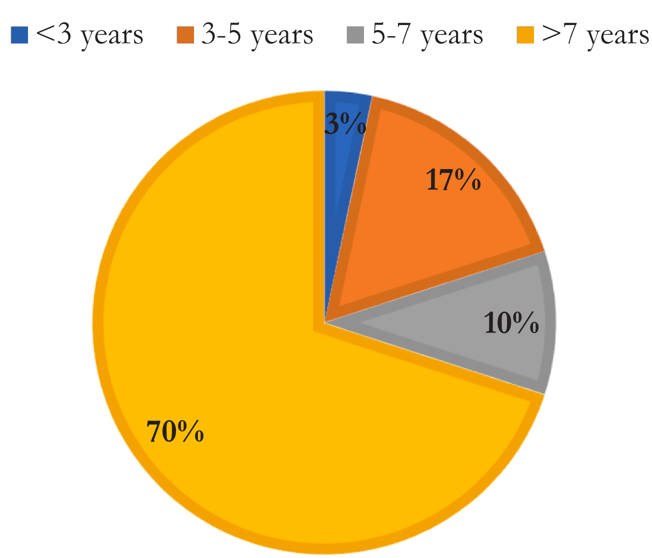

Figure A 3.2. Work experience of respondents.

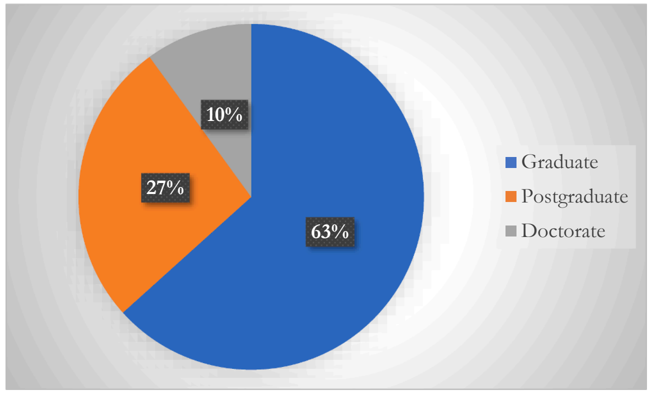

Figure A 3.3. Educational qualification of respondents.

Appendix A4a: questionnaire (for GINA)

Following are the sub-enablers identified from the literature for evaluating the enablers for resilient agri-food supply chains through industry 4.0 enabling technologies in the UAE. In the evaluation sheet, you are requested to highlight the impact of one factor over the other. You are requested to rate it on a scale of 1–5 (where 1 represents least influential and 5 represents most influential).

Sub Enablers	RTIS	EPT	IRM	PND	SS	SCS	JCP	MT	WSIR	HDPF	RAM	SMS	RSB
RTIS	1												
EPT		1											
IRM			1										
PND				1									
SS					1								
SCS						1							
JCP							1						
MT								1					
WSIR									1				
HDPF										1			
RAM											1		
SMS												1	
RSB													1

Appendix A4b: questionnaire (for FLQOWA)

In the evaluation sheet, you are requested to highlight the importance and usage of I4T corresponding to each enabler. You are requested to rate it on a scale of 1–5 (where 1 represents very low usage and 5 represents very high usage).

Sub-enablers	I4Ts									
	AM	AI	AR/VR	BDA	BCT	CC	CPPS	DT	IoT	RS
RTIS										
EPT										
IRM										
PND										
SS										
SCS										
JCP										
MT										
WSIR										
HDPF										
RAM										
SMS										
RSB										

Data availability

Data will be made available on request.

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