Operations Management Research (2024) 17:711–727
https://doi.org/10.1007/s12063-024-00444-w

What impedes digital twin from revolutionizing agro-food supply chain? Analysis of barriers and strategy development for mitigation

Vinay Surendra Yadav[1] · **Abhijit Majumdar**[2]

Received: 28 December 2022 / Revised: 23 January 2024 / Accepted: 30 January 2024 / Published online: 8 March 2024

Abstract
Digital Twin (DT) is a technology platform that is revolutionizing the supply chain digitization process by creating virtual representations of physical systems. Agro-food supply chain (AFSC) is one of the most important supply chains that can be made more efficient by widespread adoption of DT. However, the adoption and implementation of DT in AFSC is very limited due to various hindrances. Thus, it is imperative to identify and analyze the DT barriers thoroughly; and subsequently, develop strategies to overcome the dominant barriers for the successful implementation of DT in AFSC. This study identifies the barriers to DT implementation through a literature review and experts' opinions. The interaction amongst the barriers is captured using the "Weighted Influence Non-linear Gauge System (WINGS)" method. Lack of technology infrastructure, technology immaturity, and high capital investment emerge as the dominant causal barriers. Furthermore, to overcome the identified barriers, a framework based on a triple helix approach is suggested. The findings of the study will be useful for government agencies, policymakers, agricultural institutions, and agro-food industry stakeholders to eliminate the obstacles to the successful implementation of DT in AFSC.

Keywords Agro-food supply chain · Barriers · Digital twin · Digitization · Triple helix framework · WINGS method

1 Introduction

The United Nations (UN) report on Sustainable Development Goals (SDG) estimates that by 2050, the world needs to feed an additional two billion people putting a further burden on rapidly depleting natural resources. The current program to mitigate hunger is not on track and at present around 690 million people, which constitutes almost 9% of the world population, are hungry (FAO 2020). If the trend continues then the number will swell to 840 million by 2030. Thus, ensuring food security would be a challenging task for the government across the globe. Besides, developing countries will feel more heat as a large population is expected to face hunger and malnutrition defeating the purpose of SDG2, i.e., no hunger (Rockström et al. 2020). One-third of total food production is wasted in the journey of farm to fork (Gustavsson et al. 2011). Additionally, world geopolitics including war, harsh weather, and multiple shocks due to COVID-19 is further disrupting food production and thus, posing a severe threat to food security and hunger management programs. Thus, the need for new methods of food production, reduction of food wastage, and efficient management of AFSC is suggested (Kumar et al. 2022; Yadav et al. 2022). In this context, digital technologies are the rays of hope to fulfill SDG2 by ensuring food security (Kumar et al. 2023).

The important issues pertinent to AFSC can be summarised as follows: a) food waste b) hunger and malnutrition c) increased demand d) sustainability-related issues and e) factors related to the business environment such as war, geopolitics and pandemics, etc. Some of these issues (such as food waste, hunger and malnutrition, sustainability, etc.) can be addressed through proper monitoring while the other issues (such as increased demand, etc.) can be addressed to a certain extent by optimizing the various AFSC processes. In both cases whether monitoring or optimization of AFSC processes, the role of digitization is indispensable. Digitization helps the agro-food industries by creating a

✉ Abhijit Majumdar
majumdar@textile.iitd.ac.in

1 Operations and Quantitative Techniques, Indian Institute of Management Shillong, Meghalaya 793018, India

2 Department of Textile and Fibre Engineering, Indian Institute of Technology Delhi, New Delhi 110016, India

digital ecosystem where a firm's internal activities, production, development, and supply chain process are interconnected (Ribeiro-Navarrete et al. 2023). Additionally, digitization brings structural changes through leveraging digital technologies and propels economic growth by opening newer possibilities (i.e., markets), modes of delivery, and traceability along the supply chain (Ribeiro-Navarrete et al. 2023). Several researchers have already suggested that significant emphasis should be given to digitization to have better monitoring and control of various AFSC processes (Benyam et al. 2021; Lioutas et al. 2021; Yadav et al. 2022). This has been possible due to recent advancements in a series of digital technologies (Kraus et al. 2022) including digital twin (DT) which is one such emerging technology promoting digitization by making a virtual representation of objects and systems that are continuously updated in real-time with the help of machine learning, simulation and reasoning to make better decisions (Fuller et al. 2020; Tao et al. 2018). Dutta et al. (2020) and Tzachor et al. (2022) also stressed the need to implement DT to address the AFSC challenges. Furthermore, looking at the nature of AFSC which is complex, disintegrated, and has inefficient public distribution, the application of DT is a must for proper monitoring and optimization of AFSC processes (Yadav et al. 2022). DT has three parts: physical, virtual, and the connection between the two. The connection between the physical and virtual worlds is established by a series of sensors and other data collection tools. The temporal changes in the state of the physical entity are monitored through simulation, analytics, and machine learning algorithms (Majumdar et al. 2023). Additionally, IoT has been the biggest booster for the implementation of DT. This is evident from Gartner's report which states that 76% of IoT-enabled organization are already using DT or plan to do so in the next three years (Gartner 2019). Several leading organizations like General Electric, Siemens (Pylianidis et al. 2021), US Airforce, NASA (Glaessgen and Stargel 2012), PTC, Oracle, SAP, Ansys, Dassault, and Altair (Qi et al. 2018) are using DT. Some of the DT applications include product design, production planning, supply chain, man-machine interaction in workshops, predictive maintenance, power generation, construction, urban planning, prognostics, and healthcare management, etc.

The agriculture sector is a promising area where DT is believed to bring a paradigm shift. Recently, Tata Consultancy Services has built a DT-based system to monitor and estimate food freshness in real time (Dutta et al. 2020). Their system is capable of assessing the food quality by observing chemical degradation and physical property patterns via a DT platform. Besides, DT can be helpful in better prediction and management of post-harvest loss patterns which can be further utilized to enhance the shelf-life of food products and to reduce food waste. Furthermore, DT offers several applications in AFSC such as traceability, food safety, logistics, process design, process monitoring, and cold chain operations (Defraeye et al. 2021). In the Indian context, the leverage of digital technologies and other information and communication technologies (ICTs) could be realized by creating AgriStack, a platform that would suggest to the farmers what crops to grow, what seeds to buy, how to maximize the yield and when to sell the crop. For this, the Ministry of Agriculture, Government of India, is about to finalize the "India Digital Ecosystem of Architecture (IDEA)" (Beriya 2022). Furthermore, to accomplish this goal, a few pilot projects have been started by the Indian government with the support of leading agriculture technology (Agtechs) organizations. This shows that DT implementation will be in focus to realize the government's objective of delivering end-to-end services to the stakeholders. However, the implementation of DT in AFSC is still in a nascent stage and the potential of its application is yet to be fully perceived. This propels the need to understand the barriers to DT adoption and implementation in the Indian AFSC. The existing literature in this domain is limited to survey work or bibliometric analysis where few opinions have been discussed. To the best of the authors' knowledge, no work has yet been performed to study the DT adoption and implementation barriers in the Indian AFSC. Therefore, this study intends to address the following key research questions:

RQ1: *What are the barriers impeding the implementation of DT in the Indian AFSC?*
RQ2: *What kind of interrelationships prevail among these barriers?*
RQ3: *What strategies should be adopted to overcome these barriers for the successful implementation of DT in AFSC?*

By answering the above research questions, the present work aims to contribute to the literature on the adoption and implementation of DT in the Indian AFSC. The knowledge of important barriers and their interactions with each other would help the concerned stakeholders in the assessment of their readiness towards reaping the benefits of DT. Moreover, to cope with the identified barriers, the present work also proposes the application of the Triple Helix Framework linking the actions needed by industry, academia, and government.

2 Literature review

The concept of DT was first hypothesized by Yale University Scientist David Gelernter in 1991. However, it was Dr. Michael Grieves of the University of Michigan who applied the concept in manufacturing and formally defined the DTs in 2003. Later in 2012, "The National Aeronautics and Space Administration (NASA)" revisited the concept of DT and defined it as a "multi-physics, multiscale, probabilistic, ultra-fidelity simulation that reflects, in a timely manner, the state of a corresponding twin based on the historical data, real-time sensor data, and physical model" (Glaessgen and Stargel 2012). Another important definition of DT is recently given by Verdouw et al. (2021) which considers DT as "a dynamic representation of a real-life object that mirrors its states and behavior across its lifecycle and that can be used to monitor, analyse and simulate current and future states of and interventions on these objects, using data integration, artificial intelligence and machine learning." DT is also known by names such as digital mirror, digital shadow, virtual avatar, virtual phantom, or synchronized digital prototype (Defraeye et al. 2021).

2.1 Application of DT in AFSC

DT is a recent technological development and hence limited applications have been observed in the AFSC. Pylianidis et al. (2021) identified 28 use cases of DT in the agriculture sector and compared them with the use cases of other sectors by performing a detailed literature survey. Additionally, the authors discussed the adoption of DT in the agriculture sector by analyzing technology readiness levels, reported benefits, and service categories. Henrichs et al. (2022) conducted a literature review to understand the applications, challenges, and opportunities of DT in the food industry. The authors found that the usage of DT is mainly focussed on the production and processing stages of AFSC while other stages of AFSC are rarely studied. The collection and processing of large data in real time pose significant challenges to implementing the DT system in AFSC. Furthermore, the current technological landscape is yet to be fully matured and the lack of a digital infrastructure ecosystem is the major reason for the slow progress of DT applications in AFSC. Verdouw et al. (2021) discussed the application of DT for smart farming and proposed a conceptual framework for farm management. The authors showed the applicability of their designed DT system through five use cases on dairy, arable crops, horticulture, livestock, and vegetable farming.

Food loss is a significant concern for industries, governments, and researchers around the world (Yadav et al. 2022) since it poses a major threat to food security and sustainability. DT can greatly help in this aspect by modeling the temperature-dependent food loss at each stage of AFSC while simultaneously predicting and recording the parameters for better refrigeration to reduce further food loss (Defraeye et al. 2019). Burgos and Ivanov (2021) utilized anyLogistix supply chain DT to study the operations and performance dynamics of the COVID-19 pandemic situation in Germany. The authors created a discrete-event simulation method and found that resilience is severely affected by the intensity of the pandemic and associated activities such as lockdowns, customers' behavior, and inventory-ordering dynamics. In such a context, supply chain DT and end-to-end visibility are viable approaches along with resilient demand, capacity, and inventory management (Hald and Coslugeanu 2022; Ivanov and Dolgui 2022). The application of DT to the fresh horticulture supply chain was studied by Defraeye et al. (2021). These applications include cold chain monitoring, food traceability, food safety, product and process design, and supply chain logistics. Melesse et al. (2022) showed the application of DT for reducing food waste by monitoring the freshness of produce. The authors developed a machine learning (ML) based DT that monitored the quality of banana fruit throughout its storage lifecycle. Shoji et al. (2022) created a COMSOL multiphysics-based DT to map the postharvest life of fruit imported from Spain to Switzerland. Their study tracked 331 cold-chain shipments comprising raspberry, strawberry, eggplant, and cucumber throughout the precooling, distribution, and retail stores stage of the supply chain. A few important applications of DT for various AFSC processes are listed in Table 1.

2.2 TOE framework

The "Technology-Organization-Environment (TOE)" is a theoretical framework developed by Tornatzky and Fleischer (1990) to study the implementation and adoption of technological innovations. Technology aspects (both internal and external) are evaluated under a technological context while organizational characteristics including structure, culture, and resources are described under organizational aspects. The environmental context takes into account elements such as composition, size, and competitors of the firm, the regulatory environment, and the macroeconomic factors. In information system literature, the TOE framework is often utilized for studying technology adoption (Gangwar et al. 2015). A few recent applications of the TOE framework include big data analytics (Verma and Bhattacharya 2017), customer relationship management (Cruz-Jesus et al. 2019), augmented reality (Masood and Egger 2020), blockchain (Kamble et al. 2021; Ganguly 2022), and smart manufacturing (Shukla and Shankar 2022). Verma and Bhattacharya (2017) studied the influence of TOE factors on perceived strategic value for the adoption of big data analytics. The findings of the study confirmed that the non-realization of strategic value is the major hindrance in the adoption of big data analytics. Cruz-Jesus et al. (2019) utilized the TOE framework to assess the adoption of customer relationship management which suggests that each aspect of the TOE dimension affects the adoption stages differently. Masood and Egger (2020) used the TOE framework as a theoretical basis for investigating the critical success factors and

Table 1 Summary of DT applications for various AFSC processes

Sl. No.	Authors	Country	Approach	Area
1	Defraeye et al. (2019)	South American & European countries	Simulation and statistical analysis	Food loss in refrigerated mango fruit supply chain
2	Burgos and Ivanov (2021)	Germany	Discrete-event simulation on AnyLogistix software	Impact of COVID-19 and resiliency in the food supply chain (FSC)
3	Dutta et al. (2020)	India	DT platform	Food freshness monitoring
4	Wang et al. (2020)	--	Simulation	End-to-end visibility in FSC
5	Coelho et al. (2021)	Portugal	Simulation	Cross-docking distribution facility for perishable produce
6	Defraeye et al. (2021)	--	Conceptual	Fresh horticulture produces
7	Tebaldi et al. (2021)	--	Literature review	General overview of DT in AFSC
8	Vallejo et al. (2021)	Mexico	Simulation and agent modelling	Resiliency in local FSC
9	Verdouw et al. (2021)	Netherlands, Spain, and Belgium	Implementation, design, and multiple case analysis	Smart farming
10	Henrichs et al. (2022)	--	Literature review	Application of DT in FSC
11	Melesse et al. (2022)	--	Deep-convolution neural network-based machine learning approach	Food quality monitoring
12	Shoji et al. (2022)	Spain and Switzerland	Simulation using COMSOL multiphysics and statistical analysis	Postharvest losses in the fruit supply chain

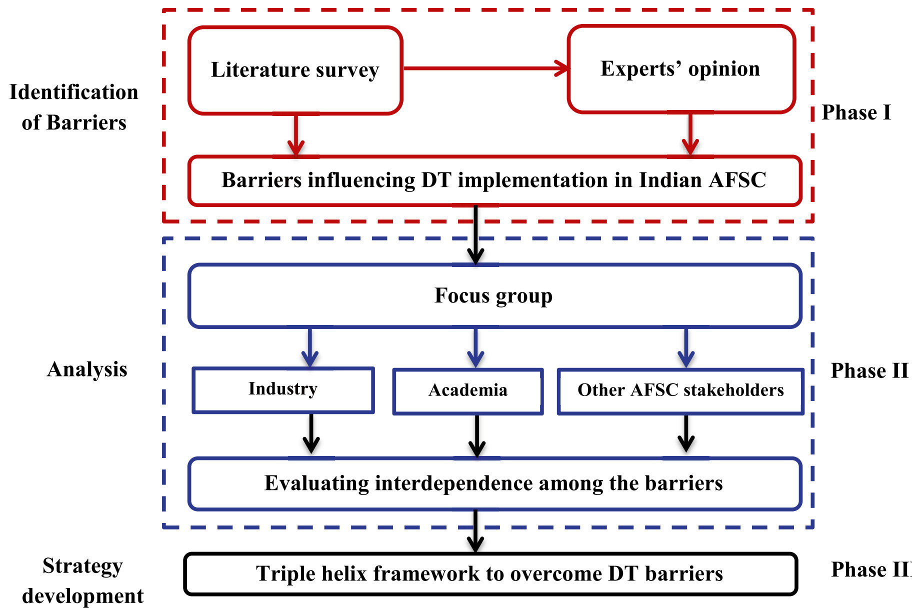
challenges of augmented reality adoption for industrial digitization. The results showed that technological factors are more important while organizational issues as more relevant for industries. Kamble et al. (2021) investigated blockchain adoption behavior through the theoretical lens of the TOE and the technology acceptance model. The study revealed that partner readiness, competitor pressure, perceived ease of use, and perceived usefulness are the dominant influencing constructs for blockchain adoption. Likewise, Ganguly (2022) has utilized the TOE framework to categorize the challenges of blockchain adoption in the logistics sector. Kinkel et al. (2022) applied TOE prerequisites to study the AI technologies adoption in manufacturing and observed that a few organizational factors like digital skills, size of the company, and R&D intensity have a greater impact on AI implementation in manufacturing. Later on, Shukla and Shankar (2022) used an extended TOE framework to classify the critical success factors for the adoption of smart manufacturing in Indian SMEs. Therefore, the utility of the TOE framework provoked us to utilize it for the categorization of identified DT barriers in this work.

3 Research methodology

The present work was carried out in three phases. In the first phase, a literature search was performed using online databases such as Scopus, Web of Science, EmeraldInsight, IEEE Explore, ScienceDirect, and Google Scholar with keyword combinations ("Barriers" OR "Challenges" OR "Obstacles" OR "Hindrances") AND "Digital Twin" AND ("Agriculture Supply Chain" OR "Food Supply Chain" OR" Agro-Food Supply Chain"). The literature obtained from these searches was refined and read by at least one of the authors to identify the critical barriers to the implementation of DT in AFSC. Thus, barriers identification under TOE dimension involved two processes where literature screening was adopted in first step while expert's opinion in form of focus group was used in second step. Moreover, focus group was utilised for three purposes i.e., barriers finalisation, data collection for WINGS method and attainment of insights for formulation of strategies to eliminate the identified barriers. The details of focus group domain experts are provided in the next section. Focus group was considered to be suitable for this study over experts' interviews since conflicting opinions in focus group could easily be deliberated which helps in reaching to a consensus. On contrary, attaining consensus on conflicting scenario is hard in case of experts' interviews. Another reason includes the newness of considered topic where open-ended discussion among the domain experts could bring better clarity about the constructs to understand the underlying complexity of driver-driven relationships. This led to the finalization of 15 barriers classified under the TOE framework through consensus amongst the experts. This was followed by the application of the WINGS method for modeling identified barriers in the second phase. Finally, in the third phase, a Triple Helix Framework was developed to overcome these barriers. The details of the research framework are shown in Fig. 1.

The *RQ2* is related to evaluating the interrelationship between the DT barriers in the context of Indian AFSC.

Fig. 1 Research framework



"Interpretative Structure Modeling (ISM)", "Total Interpretative Structural Modeling (TISM)", "Decision Making Trial and Evaluation Laboratory (DEMATEL)" and WINGS are some of the approaches that can be used for this purpose. However, ISM and TISM only consider whether an interrelationship exists or not without considering the intensity of interrelationship and hence, would not be apt to answer *RQ2*. On the other hand, DEMATEL is an approach that creates a structural model through diagraphs and matrices and also provides intensity between the elements under study. However, it only considers the influencing intensity of an element while ignoring its strength (internal importance or power of a construct). This limitation of DEMATEL is resolved in the WINGS method by considering both influence intensity and strength of an element. It is evident that whenever an interaction exists, both internal strength as well as influencing intensity of a construct become important in a structural model (Govindan et al. 2023). Michnik (2013), the inventor of the WINGS method underpinned this with two analogical laws, i.e., laws of gravitation and Coulomb's law. The impact in an elastic collision depends on both the velocity and mass of colliding objects. Similarly, the magnitude of the Coulombic force of attraction is dependent on masses (charges) as well as the distance between them (Michnik 2013). However, the WINGS method may suffer from subjectivity that cannot be eliminated completely wherever human judgments are involved. However, the effect can be minimized by involving multiple experts and the same was adopted in this work. Various AFSC stakeholders having different priorities were included as experts, and their ratings on strength and influencing intensities were averaged leading to a reduced effect of subjective weighting.

Several applications of WINGS method have been reported in fields like project selection (Michnik 2018), reverse logistics (Kaviani et al. 2020), green supply chain (Wang et al. 2021), blockchain in healthcare (Govindan et al. 2023), and industrial symbiosis (Yadav and Majumdar 2023). As DT is a new technology platform, it requires an understanding of both the strength and influencing intensity of the barriers and hence, the WINGS method was chosen to study the barriers of DT in the Indian AFSC. The steps of the WINGS methodology are as follows:

Step 1: Identification of constructs (barriers) within the scope of the study: This is done through suitable approaches like literature search, questionnaire survey, and experts' opinions.

Step 2: Determination of the causal relationship between the elements: Interdependencies are evaluated using a causal relation graph (Michnik 2013). Causal relationships are represented through arrows.

Step 3: Determination of strength and intensity of influence: Linguistic expressions [No (N) - 0; Very low (VL) - 1; Low (L) - 2; High (H) - 3; Very high (VH) - 4] are used for determination of strength of constructs as well as intensity of influence on other constructs.

Step 4: Formulation of "average direct strength-influence matrix (D)" having elements as d_{ij}: where the dimension of the matrix is equal to the number of elements (n). The strength components are filled as the diagonal element of the matrix while the intensity of influence of element 1 on element 2 is kept in row 1 and column 2 of matrix

D. Thereafter, the responses of experts are averaged. The matrix thus obtained is utilized in the next step for normalization.

Step 5: Normalization of average direct strength-influence matrix (D): The normalization is carried out by using equation 1.

$$S = \frac{D}{h} \tag{1}$$

where $h = \sum_{i=1}^{n} \sum_{j=1}^{n} d_{ij}$ and S is the normalized matrix, and d_{ij} is the element corresponding to the ith row and jth column of average direct strength-influence matrix D.

Step 6: Estimation of "total strength-influence matrix (T)": This is obtained by using the equation 2.

$$T = S(I - S)^{-1} \tag{2}$$

Here, I is an identity matrix having a dimension equal to the number of constructs.

Step 7: Estimation of different indicators: Total impact (x_a) and total receptivity (y_b) are the sum of all the elements in a row and a column, respectively, of the total strength-influence matrix (T). Thereafter, the ranking of constructs is performed based on the indicators x_a, y_b, $(x_a + y_b)$ and $(x_a - y_b)$.

4 Data collection and analysis

Purposive sampling was used to select the experts for this study and targeted individuals who meet the desired criteria were contacted. DT being an emerging area, the number of individuals having expertise in DT was relatively small. Therefore, to increase the pool of experts, we tried our extended network and contacted a total of 34 experts through LinkedIn, email, and personal phone calls. Out of these, 12 experts agreed to participate in the focus group conducted using an online platform. All the experts had acquaintance or experience in the implementation of DT projects, small or big, and they were aware of DT implementation issues. The selection of experts ranging from managers to farmers helped to incorporate the opinions of all AFSC stakeholders. The list of barriers was presented and discussed with the experts. The experts were then asked to express their opinion about the influence of each barrier over the remaining 14 barriers using verbal ratings of no (N); very low (VL); low (L); high (H); very high (VH) as explained in previous section. The details of the experts considered in this study are mentioned in Table 2.

The details of barriers identified from the literature and ratified by the domain experts are elaborated in Table 3. Most of the barriers fall under the technological category followed by environmental and organisational. The data obtained from the experts were aggregated to determine "average direct strength-influence matrix (D)" as shown in Appendix (Table A1). Following the WINGS method, this matrix was normalized using equation 1 to get the normalized matrix as given in Table A2, Appendix. Thereafter, equation 2 was used to get the "total strength-influence matrix (T)" that is shown in Table 4. Furthermore, Table 4 was also utilized to obtain various indicators like the summation of row elements for a particular construct known as *total impact* and column summation known as *total receptivity*. The summation of rows and columns and the difference between them, for a construct, is known as *total engagement* and *role*, respectively. Furthermore, these parameters are used to rank the barriers to DT implementation as shown in Table 5. The *role* value is used for the categorization of barriers into two groups, namely cause and effect.

Table 2 Details of focus group experts

	Number of Experts
Gender	
Male	8
Female	4
Practical experience with DT	
0-2 years	1
2-4 years	2
4-6 years	6
6 years or more	3
Expertise details	
Industry – CEO, CTO	3
Industry – Production engineer, senior manager, SC analyst	3
Other stakeholders – Farmers, middlemen, consumer	3
Academia – Professor, postdoctoral researcher	3

5 Results

This section deals with *RQ1*. Table 5 shows the ranking of barriers based on various scores. While the engagement score, i.e., the sum of impact and receptivity scores, indicates the importance of a barrier, the role score implies the capacity of a barrier to influence other barriers. If the role score is positive then the barrier belongs to the cause-group and vice versa. Seven barriers were categorized into cause-group while eight barriers were categorized into effect-group. High capital investment (DTB10), technology immaturity (DTB6), lack of organizational readiness (DTB12), challenge to integrate internal digital ecosystem with external supply chain (DTB3) and lack of standardization

Table 3 List of barriers and their description

Sr. No.	Digital twin barriers (DTB)	Category	Description	Sources
1.	Lack of interoperability (DTB1)	T*	Each component of the system needs to be interconnected with the whole network to ensure the proper execution of tasks in DT. Such large interconnections bring severe complexities and limit the scalability and thus, pose a critical challenge for DT implementation.	Henrichs et al. (2022); Kamble et al. (2022); Semeraro et al. (2021); Werner et al. (2020)
2.	Lack of technology infrastructure (DTB2)	T	DT requires infrastructure that should be interoperable with other systems. Indian AFSC lacks technology infrastructure and follows traditional methods. Thus, the updation of machines, processes, and technologies is necessary which further needs large capital investment.	Experts' opinion
3.	Challenge to integrate internal digital ecosystem with external supply chain entities (DTB3)	T	To operate DT throughout the product lifecycle, there is a need to integrate the internal digital ecosystem with external supply chain entities which is a tedious task. In addition to this, the complex and disintegrated nature of the Indian AFSC adds to further challenges in achieving the integration of physical and digital supply chains.	Kamble et al. (2022); Perno et al. (2022); Werner et al. (2020); Yadav et al. (2022)
4.	Multidisciplinarity (DTB4)	E	DT requires expertise from multi-disciplinary fields having their own individual goals, and alignment of work schedules and common goal attainment is difficult.	Fuller et al. (2020); Henrichs et al. (2022); Rasheed et al. (2020); Yadav et al. (2022)
5.	Lack of standardization (DTB5)	T	Indian AFSC is complex, disintegrated, and involves several intermediaries which leads to a lack of standardization of processes. There is no uniform protocol for operations, data storage and exchange, etc. This leads to difficulties in implementing the DT project.	Fuller et al. (2020); García et al. (2022); Perno et al. (2022); Semeraro et al. (2021); Singh et al., (2018); Werner et al. (2020); Yadav et al. (2022)
6.	Technology immaturity (DTB6)	T	Some of the emerging technologies needed for DT are still evolving and therefore, the users fail to explore the full potential of the technology. In addition to this, digital readiness and technological infrastructure vary for each stakeholder of Indian AFSC.	Experts' opinion
7.	Security and privacy concerns (DTB7)	T	Incompatibility with IoT devices or supporting systems may pose a serious threat to the security of DT systems. Any security breach would result in loss of privacy leading to loss in revenue and reputation.	Fuller et al. (2020); Perno et al. (2022); Rasheed et al. (2020); Singh et al. (2018); Werner et al. (2020)
8.	Real-time data processing capability (DTB8)	T	Large variety, volume, and speed of data, spatiotemporal resolution of sensor data, communication lag, and fast archival retrieval limit the real-time data processing capability of DT systems.	García et al. (2022); Rasheed et al. (2020); Werner et al. (2020)
9.	Scalability challenges (DTB9)	T	The level of complexity and lack of technology infrastructure limit the scalability of DT systems.	Henrichs et al. (2022); Singh et al. (2018)
10.	High capital investment (DTB10)	O	Upgradation of technology and infrastructure for the implementation of the DT systems requires significant capital investment. Most of the Indian farmers have small pieces of land and their socio-economic conditions do not allow them to invest in technologies like DT.	Pylianidis et al. (2021); Werner et al. (2020); Yadav et al. (2022)

Table 3 (continued)

Sr. No.	Digital twin barriers (DTB)	Category	Description	Sources
11.	Resistance from stakeholders (DTB11)	O	India has a glorious past in farming and associated activities and Indians are accustomed to those traditional practices. New technologies and practices bring different challenges and demands for process transformation. However, due to a lack of understanding and uncertainty about the outcome of these changes, fear amongst the AFSC stakeholders is created and hence, resistance is observed against any technological transformation and DT is no exception.	Experts' opinion
12.	Lack of organizational readiness (DTB12)	O	The knowledge and competencies of the employees in using ICT are heterogeneous and hence, it is a roadblock to full capacity utilization of the DT system. Indian food-industries operate on small profit margins and hence, their investment capacity in technological infrastructure is limited which further limits the organisational readiness towards DT.	Henrichs et al. (2022); Perno et al. (2022); Yadav et al. (2022)
13.	Lack of required skillsets (DTB13)	E	Not all stakeholders of AFSC (for example, Indian farmers and middlemen between farmers and government regulated markets) are tech-savvy and hence, limit the scope of DT implementation.	García et al. (2022); Henrichs et al. (2022)
14.	Absence of physicochemical models (DTB14)	T	The simulation of food processing and food storage requires the knowledge of several food properties that are very hard to predict or calculate. This limited knowledge about the chemical and kinetics of biological processes further makes it difficult to develop physicochemical models.	Henrichs et al. (2022)
15.	Complexity of food systems (DTB15)	T	The variability in environmental conditions requires DT to improve continuously. In addition, perishability, limited shelf life, changing behaviour, and customs requirements of consumers increase the complexities in the design of the DT system.	Henrichs et al. (2022); Pylianidis et al. (2021)

**T* Technology, *O* Organizational, *E* Environment

Table 4 The total strength-influence matrix

	DTB1	DTB2	DTB3	DTB4	DTB5	DTB6	DTB7	DTB8	DTB9	DTB10	DTB11	DTB12	DTB13	DTB14	DTB15	**R**
DTB1	0.0063	0.0050	**0.0070**	0.0037	**0.0079**	0.0046	0.0055	0.0057	0.0041	0.0046	0.0006	0.0052	0.0037	0.0002	0.0002	0.0642
DTB2	**0.0081**	**0.0081**	**0.0079**	0.0031	0.0066	**0.0072**	0.0065	**0.0070**	**0.0076**	0.0013	0.0048	**0.0081**	0.0050	0.0041	0.0031	0.0886
DTB3	0.0048	0.0011	**0.0072**	0.0061	0.0026	0.0009	0.0035	**0.0074**	0.0055	0.0048	0.0057	**0.0079**	0.0004	0.0002	0.0006	0.0587
DTB4	0.0031	0.0007	0.0059	0.0039	0.0035	0.0022	0.0024	0.0024	0.0009	0.0037	0.0020	0.0048	0.0039	0.0015	0.0030	0.0439
DTB5	0.0052	0.0013	0.0057	0.0017	**0.0070**	0.0033	0.0050	0.0065	0.0057	0.0041	0.0026	0.0039	0.0042	0.0037	0.0037	0.0635
DTB6	0.0052	0.0009	**0.0087**	0.0004	**0.0072**	**0.0079**	**0.0085**	**0.0085**	**0.0085**	0.0035	0.0055	**0.0072**	0.0061	0.0037	0.0035	0.0853
DTB7	**0.0072**	0.0009	0.0061	0.0006	**0.0079**	0.0046	**0.0070**	0.0063	**0.0078**	0.0039	0.0065	**0.0070**	0.0031	0.0011	0.0042	0.0742
DTB8	**0.0074**	0.0017	0.0050	0.0007	0.0061	0.0037	0.0039	**0.0083**	0.0057	0.0050	0.0009	**0.0072**	0.0037	0.0011	0.0007	0.0611
DTB9	0.0033	0.0006	0.0046	0.0022	0.0024	0.0004	0.0052	0.0007	0.0063	**0.0074**	0.0007	0.0022	0.0004	0.0044	0.0046	0.0454
DTB10	0.0059	**0.0089**	0.0057	0.0006	0.0037	**0.0076**	**0.0070**	0.0065	**0.0070**	**0.0078**	**0.0079**	0.0059	0.0063	0.0022	0.0028	0.0857
DTB11	0.0004	0.0042	0.0054	0.0055	0.0041	0.0039	0.0035	0.0030	0.0041	**0.0070**	0.0061	0.0046	0.0044	0.0006	0.0002	0.0569
DTB12	0.0066	0.0044	0.0039	0.0004	0.0046	0.0004	0.0009	0.0006	**0.0070**	0.0042	0.0054	**0.0076**	0.0065	0.0041	0.0024	0.0589
DTB13	0.0031	0.0017	**0.0074**	0.0022	0.0054	0.0041	0.0050	0.0063	0.0063	0.0035	0.0061	0.0037	0.0065	0.0028	0.0041	0.0679
DTB14	0.0037	0.0037	0.0039	0.0022	**0.0072**	**0.0078**	0.0007	0.0046	0.0042	0.0046	0.0013	**0.0078**	0.0063	0.0057	**0.0068**	0.0705
DTB15	0.0044	0.0044	0.0042	0.0030	0.0044	**0.0074**	0.0044	0.0046	0.0042	0.0041	0.0028	**0.0079**	**0.0078**	0.0046	**0.0068**	0.0751
C	0.0748	0.0476	0.0886	0.0362	0.0807	0.0659	0.0690	0.0783	0.0849	0.0694	0.0589	0.0910	0.0681	0.0399	0.0467	$\lambda =$ **0.0068**

λ = threshold value for significant relationship = average of matrix T + 1 × standard deviation

(DTB5) are the top five barriers in terms of total engagement, i.e., importance. On the other hand, lack of technology infrastructure (DTB2), absence of physicochemical models (DTB14), complexity of food systems (DTB15), technology immaturity (DTB6), and high capital investment (DTB10) are the top five barriers in terms of role, i.e., influence. It is important to note here, that the rankings of barriers in terms of total impact and role have a good agreement as four (DTB2, DTB10, DTB6, and DTB15) barriers are found to be common in the list of top-five barriers in both cases. Technology immaturity (DTB6) and high capital investment (DTB10) are occupying higher ranks in terms of engagement and role, and both of them emerge as cause-group barriers. Therefore, these barriers require more attention and care for the successful adoption and implementation of DT in AFSC.

To answer *RQ2*, an influence map showing the significant driver-driven relationships among the barriers was developed. For this, the "average of total strength-influence matrix + 1 × standard deviation" was used as the threshold value (0.0068). A relational value in Table 4 above this threshold implies a significant causal relationship. The pictorial representation of the influence map is shown in Fig. 2. It is observed that lack of technology infrastructure (DTB2), technology immaturity (DTB6), and high capital investment (DTB10) are the significant cause-group barriers influencing a large number of other barriers. This is in agreement with the ranking of barriers (1, 3, and 2 respectively) in terms of the impact score shown in Table 5. Lack of technology infrastructure (DTB2) is influencing six barriers, namely lack of interoperability (DTB1), challenge to integrate internal digital ecosystem with external supply chain (DTB3), technology immaturity (DTB6), real-time data processing capability (DTB8), scalability challenges (DTB9) and lack of organizational readiness (DTB12). DT requires sensors, actuators, automated robots, high-speed computation, and information and communication technology (ICT) infrastructure. The lack of DT infrastructure will limit the integration of internal processes with external supply chain activities. Besides, the lack of high-speed computation facilities limits the capability to process the big-data in real-time raising the question of the scalability of the DT platform. As this infrastructure is scarce at present in the Indian AFSC, it slows down the maturity of DT technologies, as more use of technology and feedback from the users leads to faster maturity of technologies. All these things collectively thwart the organizational readiness to adopt and implement DT. Technology immaturity (DTB6) is also influencing six other barriers, namely the challenge to integrate the internal digital ecosystem with the external supply chain (DTB3), lack of standardization (DTB5), security and privacy concerns (DTB7), real-time data processing capability (DTB8), scalability challenges (DTB9) and lack of organizational readiness (DTB12). It

Table 5 Ranking of barriers based on various indicators

Barriers	Total impact (x_a)	Total receptivity (y_b)	Total engagement ($x_a + y_b$)	Role ($x_a - y_b$)	Group
DTB1: Lack of interoperability	8	6	8	10	Effect
DTB2: Lack of technology infrastructure	1	12	9	1	Cause
DTB3: Challenge to integrate internal digital ecosystem with external supply chain	12	2	4	12	Effect
DTB4: Multidisciplinarity	15	15	15	6	Cause
DTB5: Lack of standardization	9	4	5	11	Effect
DTB6: Technology immaturity	3	10	2	4	Cause
DTB7: Security and privacy concerns	5	8	6	7	Cause
DTB8: Real-time data processing capability	10	5	7	11	Effect
DTB9: Scalability challenges	14	3	11	14	Effect
DTB10: High capital investment	2	7	1	5	Cause
DTB11: Resistance from stakeholders	13	11	13	9	Effect
DTB12: Lack of organizational readiness	11	1	3	13	Effect
DTB13: Lack of required skillsets	7	9	10	8	Effect
DTB14: Absence of physicochemical models	6	14	14	2	Cause
DTB15: Complexity of food systems	4	13	12	3	Cause

is pertinent to note here that some of the DT technologies like micro-and nano-sensors and algorithms like artificial intelligence (AI) and machine learning (ML) are still evolving at a very rapid pace. Technology immaturity limits the capability to process the real-time big-data which affects the scalability of DT within the AFSC network and often hinders the integration of internal and external supply chains. Moreover, technology immaturity may lead to a lack of standardization causing security and privacy issues in the DT network. High capital investment (DTB 10) influences five barriers, namely lack of technology infrastructure (DTB2), technology immaturity (DTB6), security and privacy concerns (DTB7), scalability challenges (DTB9), and resistance from stakeholders (DTB11). DT systems and

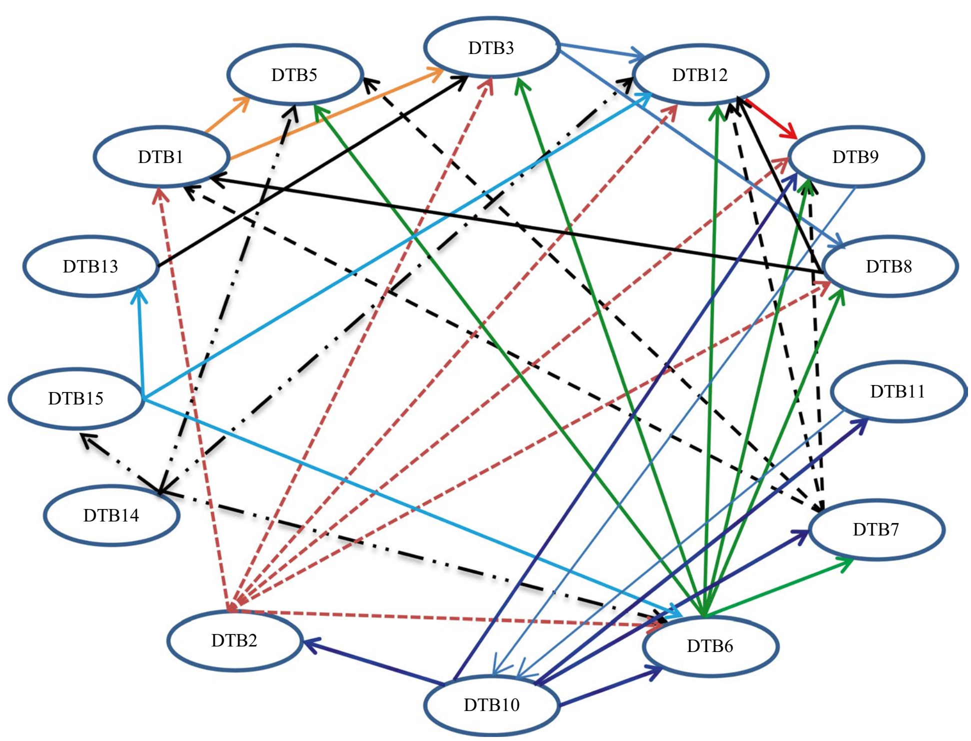


Fig. 2 Influence map of DT barriers

technologies like intelligent robots, smart machines, AI and ML systems, high-speed internet connectivity, and 3D simulation software require high upfront capital investment as well as recurring costs for maintenance and upgradation. In general, the price-sensitive AFSC faces challenges to attract this investment hampering the growth of DT infrastructure and technology maturity, the two other important cause-group barriers. Investment in the latest technologies can make the DT system more secure against hacking and unwarranted access eliminating the resistance of stakeholders. Here, the role of government and public-private partnerships will become crucial to support such large financing. The absence of physicochemical models (DTB14) and the complexity of food systems (DTB15) are influencing four and three barriers, respectively. These two barriers ranked 2nd and 3rd respectively in terms of role score, are intrinsic to the processes and systems of AFSC. Therefore, more investment in research is needed so that improved physiochemical process models can be developed.

6 Discussion

Several authors have focused on the need to implement DT in AFSC. Tzachor et al. (2022) emphasized implementing DT to address the challenges related to food waste, hunger, sustainability, greenhouse gases, etc. Dutta et al. (2020) focused on developing DT based platform to prevent food wastage by estimating and monitoring the freshness of produce in real-time. However, the readiness and adoption of DT in the Indian AFSC are still in the nascent stage due to various impediments that have been analyzed in this research. Lack of technology infrastructure (DTB2), technology immaturity (DTB6), and high capital investment (DTB10) are found to be important barriers in terms of impact as well as causal role. The operationalization of DT requires multiple enabling technologies such as sensors, AI, cloud computing, simulation, visualization, and advanced analytics (Tozanli and Saénz 2022). Pylianidis et al. (2021) found that there are fewer use cases of DT in AFSC as compared to service sectors of other domains due to the lack of technological infrastructure in agriculture. Additionally, for the smooth functioning of the DT system, enabling technology infrastructure is required which needs significant upfront capital investment. Therefore, the assessment should be made to appraise whether the implementation of DT will yield tangible benefits or not (West and Blackburn 2017). Literature also suggests that most of the DT applications are in the primary stages in the agriculture sector due to technology immaturity (Pylianidis et al. 2021). Therefore, the findings of our research are in agreement with those of other researchers. According to role indicators, two important barriers to implementing DT are the absence of physicochemical models (DTB14) and the complexity of food systems (DTB15) which are highly domain-specific. This is supported by Defraeye et al. (2021) who argued while exploring the implementation of DT in horticulture that the physicochemical model capturing the biochemical, microbiological, physical, and physiological processes is essential to understanding the quality loss and shelf life of fresh produce. In another study, Defraeye et al. (2019) pointed out that change in biochemical quality increases the complexity of the food system and hence, quantifying these changes to reflect a real-time DT system is strenuous. All these findings bolster the outcome of our research.

During the discussion with experts, a few important recommendations emerged that can propel the adoption and implementation of DT in the Indian AFSC. We first present these recommendations followed by the strategies suggested to fulfil these recommendations.

Short-term recommendation 1: Develop low-cost DT solutions Short-term recommendations should be attainable within the time span of 1-2 years. In the existing socio-economic scenario, for some of the AFSC stakeholders like farmers, it is very difficult to implement DT at the grassroots due to lack of affordability. Expert 7 in this study who is a farmer stated, "*I am not good at technology and affordability is a big issue as my income is not enough*." On similar line Expert 8 (a middleman) added that, "*technology is difficult to understand and but once understood, it increases my working efficiency*." Additionally, most of the farmers and middlemen in Indian AFSC are not technology savvy. Thus, low-cost solutions with special attention to ease of use should be developed. For example, developing cheaper and more durable sensors, provision of sharing real-time simulation software and computing capability, low-cost connectivity, and availability of freely accessible information databases, etc. should go a long way for DT adoption and implementation. Expert 2 (CTO 1) supported this claim, "*I feel low-cost solution will encourage the AFSC stakeholders to implement digitization in their workplace*."

Short-term recommendation 2: Develop agro-food technology infrastructure Lack of technology infrastructure and high capital investment for infrastructural development are observed as dominant cause-group barriers. Therefore, agro-food organizations should have a technology strategy for the incorporation of sensors, IoT devices, wireless networks, 5G connectivity, simulation software, and secure information systems, etc. in their internal processes and external supply chain activities.

Medium-term recommendation: Impart skill and training to the AFSC stakeholders Medium-term recommendations can be addressed in a timeframe of 2-5 years. At present, the awareness and competence among the AFSC stakeholders about DT is at a nascent stage. Expert 1 (CEO) stated, "*The pace of digitization in agro-food industries is quite slow*." Furthermore, DT requires advanced knowledge and skills about various enabling technologies like data science, IoT, AI, ML, simulation, etc., imparting training for the capability building of the users is essential.

Long-term recommendation: Invest in DT technology development research Long-term recommendations require 5-10 years to fructify. Most of the hindrances of DT implementation are related to technology (technology infrastructure, technology immaturity, absence of physicochemical models, etc.) and their causality is quite strong as discussed in section 5. Thus, capital investment for technology research is required to provide affordable DT platforms and solutions. Expert 5 (a senior manager) supported this argument and said, "*Unless more funds are pumped into R & D, the required technology cannot be developed*." For this, technology incubation and innovation centres, industry-academia consortiums, and agro-tech start-ups should be financially supported.

6.1 Strategies for DT implementation

This section attempts to answer *RQ3*. For the adoption and implementation of DT in AFSC, a strategy portfolio involving the agro-food industry, academia, and government is needed. Based on the open-ended discussions with the domain experts, we posit a Triple Helix Framework of strategies for overcoming the important cause-group barriers identified earlier (Ivanova and Leydesdorff 2014). The actors, namely industry, academia, and government should perform a few distinct and independent tasks while there must exist some interaction between the actors with the common goal of eliminating the barriers (Lepore et al. 2022; Majumdar et al. 2021). The Triple Helix Framework depicting the distinct functions of each actor and their interactions is shown in Fig. 3.

6.1.1 Strategies for agro-food organizations

Agro-food industries should shun the risk-averse psyche and be proactive in investing part of their revenue in augmenting the technology infrastructure. Besides this, expert 1 (a CEO) stated that, "*As DT implementation requires new skillsets related to data science, simulation, automation, AI, etc., recruiting competent manpower and continuous training and development of the existing workforce should be an integral part of the organization's HR strategy*." This will augment the confidence of internal stakeholders and thus, improve the organizational readiness to adopt DT.

6.1.2 Strategies for academia

Expert 11 (professor 2) proposed that, "*The academia should primarily focus on fundamental R&D related to DT*

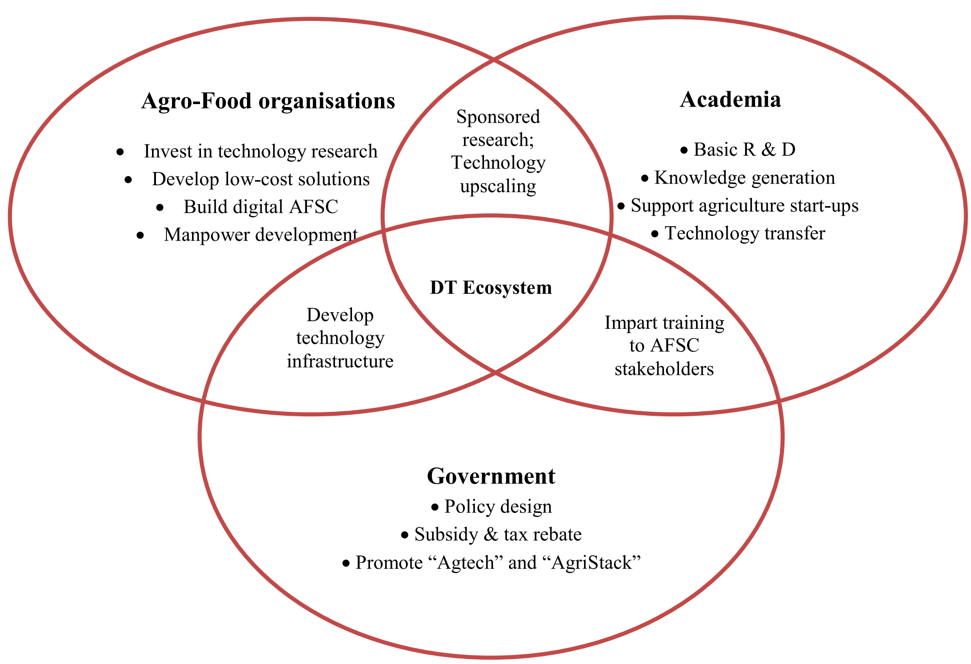


Fig. 3 Triple Helix Framework to address the DT barriers

technologies (smart sensors, robots, large-scale simulations, AI, and ML) to generate new knowledge and facilitate the agro-food industry by transferring both knowledge and skills." Besides, while analyzing the barriers, it was found that the absence of physiochemical models related to agro-food systems is largely missing. The development of such models needs a fundamental understanding of the interactions of several variables and parameters. These complicated process models can only be developed by the academia by conducting basic R&D.

6.1.3 Strategies for government

The role of government is of paramount importance in the context of DT. As the successful adoption and implementation of DT will pave the way for the food security of millions of people, the government must champion this initiative. Expert 12 (postdoctoral researcher) feels that, creation of "AgriStack" would boost agro-infrastructure. For this, collaboration with leading "Agtechs" organizations must be initiated by the Indian Government. Additionally, the government should work on regulation aspects of data security and information sharing. Likewise, the digital ethics concerns of each stakeholder must be taken care of by the regulation. Expert 1 (CEO) argued that, "*The government should offer tax rebates and subsidies to the organizations willing to invest in DT technologies so that agro-food organizations can invest more in technology infrastructure and manpower development*." The development of infrastructure requires significant capital investment and hence, the efforts by any single actor would not be sufficient therefore three-way collaboration needs to be realized for the development of the DT ecosystem.

6.1.4 Strategies for collaboration among the agro-food organizations, academia, and government

Implementing the aforesaid strategies in the real world might face challenges related to coordination, resource allocation, and stakeholders' commitment. For this, regular discussion amongst AFSC stakeholders, transparency in various processes, and mutual sharing of benefits would be required to create a trust-based environment. Expert 10 (professor 1) feels that, "*The agro-food industry should collaborate with academia and work on the development of low-cost indigenous technology solutions that are affordable to farmers, supply chain partners, and other stakeholders. The communication channel between the industry-academia should be open and the former must express its problems and requirements related to DT implementation*." On the other hand, industry should complement academia to upscale the models and prototypes by arranging field trials in real situations and also by providing funding for sponsored R&D wherever possible. "*Another important outreach strategy of academia should be encouraging the agro-food start-up companies by handholding them during the period of incubation*," quoted expert 12 (postdoctoral researcher). These start-up companies have a flat and flexible organizational structure and they can act as technology aggregators to catalyze the changes needed to overcome the resistance of late adopters. Government and academia can come together to impart training to the AFSC stakeholders so that the benefit of DT can be disseminated faster. The government and agro-food industry can jointly develop some clusters of organizations so that the cost of DT infrastructure can be shared and a culture of mutual learning can be inculcated for faster technology maturity. The focus should be on adopting strategies that leverage mutual benefits to all AFSC stakeholders so that they can take the initiatives to coordinate for the greater good.

6.2 Practical implications

This research is probably the first one to deal with the barriers to DT adoption and implementation in AFSC. As food security and attainment of SDG2 (no hunger) are going to receive increasing attention from policymakers and practitioners at the national and international levels, the outcome of this research will play a pivotal role in the near future. For any emerging technology, the diffusion curve is mostly loaded by the 'early majority' and 'late majority' (Rogers 2003) and DT is no exception. Therefore, policymakers and industry practitioners should make attempts so that there is a shift toward "innovators" and "early adopters". To make this happen, the dominant cause-group barriers (lack of technology infrastructure, technology immaturity, and high capital investment) should be mitigated by the judicious choice of strategies. This research also demonstrates the importance of concerted effects of industry, academia, and government for the effective adoption of DT. The present work highlights the importance of digitization and challenges involved in the transformation process due to the presence of complexity, cultural diversity, and resistance from stakeholders (Ribeiro-Navarrete et al. 2023). Additionally, the benefit of digitization is not clear to small organizations (Kraus et al. 2022). Indian AFSC has many such instances like farmers with small pieces of land, middlemen working in silos, etc. Employees may feel that digitization could lead to bureaucratic control and result in the suppression of their autonomy. On the contrary, digitization could be a driver for trust if top management provides a strong digital vision, reduces the perception of organizational politics, and ensures high-quality leader-member exchange (Lau and Höyng 2023). Top management should have long-term technology and R&D strategies which should be backed by the HR strategy to train the workforce. Industry-academia partnership for the development of low-cost DT technologies must be encouraged and the government should foster this by implementing supporting policies.

Though the present study is conducted in the context Indian AFSC which is not only vast but also diverse, a few findings emanating from this study have wider applicability to other AFSC having different structures. For example, mitigating strategies based on the Triple Helix Framework can be extended to any AFSC particularly in developing countries. Developed countries have better technological infrastructure and higher level of employees' digital readiness. However, they face more strict IT regulations and thus, this construct requires further investigation. Based on region-specific challenges, different sets of obstacles may be encountered and to cope with these challenges, concerted efforts are required from industry, academia, and government. Furthermore, the findings may be generalized by conducting empirical investigation.

7 Conclusion and future research directions

DT is set to revolutionize the process of digitization which in turn will bring several advantages to AFSC operations. The present work identifies and analyses the critical barriers to the implementation of DT in AFSC. The contribution of this work is threefold: first, extending and enriching the literature of DT through the identification of barriers in the context of developing countries. The second contribution is the development of a complete structural model and corresponding influence map of barriers showing clear cause-effect relationships. Seven barriers are categorized in the cause-group while eight barriers are grouped under the effect category. Amongst these barriers, lack of technology infrastructure (DTB2), technology immaturity (DTB6), and high capital investment (DTB10) are the dominant cause-group barriers to the implementation of DT in Indian AFSC. Hence, the maximum focus should be given to mitigate these barriers. Lack of organizational readiness (DTB12), challenge to integrate the internal digital ecosystem with the external supply chain (DTB3), lack of standardization (DTB5) and scalability challenges (DTB9) are the prominent effect-group barriers. The third contribution of this research is the development of a Triple Helix Framework, involving industry, academia, and government, to formulate strategies for overcoming the identified barriers. While academia must strive to generate new knowledge and agro-food process models through basic R&D, the industry should complement by upscaling the technology through investment in technological infrastructure. Government should act as a change agent by formulating policies including tax rebates and subsidies for the early adopters of DT.

The present research has some limitations. The work elucidates the interrelationship between identified DT barriers by employing the WINGS methodology that uses the opinions of domain experts. This necessitates subjective weighting to evaluate cause-effect relationships among barriers. Therefore, a structural model can be developed by employing large volume of empirical data to validate the findings of this study. Another limitation is the geographical context (India) of this study. Since the technological environment and the level of digital technology penetration is significantly different in various economies, thus the outcome of this research should be generalized with care and caution considering the region-specific factors. Furthermore, this study considers the entire AFSC as a single entity. However, AFSC has various stages including farming, distribution, storage, food processing, and so on. The digital technology penetration and adoption can vary widely at different stages of AFSC. Therefore, a microscopic study, focussing on different stages of AFSC, should be conducted in the future considering multi-tier AFSC and this would unearth the tier-specific challenges. A more detailed study on strategy development can be conducted to map how individual strategies will mitigate a group of DT adoption barriers. In addition to this, the role of DT can be explored for specific AFSC challenges like waste of perishable foods, food security, food safety, and sustainability monitoring. The above ideas may be translated to study the readiness of AFSC for the adoption of DT. Moreover, future research may be carried out to come up with a holistic framework relating DT enablers, DT practices, and AFSC performance through the application of either partial least square (PLS) or covariance-based structural equation modelling (SEM). Additionally, the Triple Helix Framework can be extended by incorporating society as the fourth dimension.

Appendix

Table A1 Average direct strength-influence matrix

	DTB1	DTB2	DTB3	DTB4	DTB5	DTB6	DTB7	DTB8	DTB9	DTB10	DTB11	DTB12	DTB13	DTB14	DTB15
DTB1	2.8333	2.2500	3.1667	1.6667	3.5833	2.0833	2.5000	2.5833	1.8333	2.0833	0.2500	2.3333	1.6667	0.0833	0.0833
DTB2	3.6667	3.6667	3.5833	1.4167	3.0000	3.2500	2.9167	3.1667	3.4167	0.5833	2.1667	3.6667	2.2500	1.8333	1.4167
DTB3	2.1667	0.5000	3.2500	2.7500	1.1667	0.4167	1.5833	3.3333	2.5000	2.1667	2.5833	3.5833	0.1667	0.0833	0.2500
DTB4	1.4167	0.3333	2.6667	1.7500	1.5833	1.0000	1.0833	1.0833	0.4167	1.6667	0.9167	2.1667	1.7500	0.6667	1.3333
DTB5	2.3333	0.5833	2.5833	0.7500	3.1667	1.5000	2.2500	2.9167	2.5833	1.8333	1.1667	1.7500	1.9167	1.6667	1.6667
DTB6	2.3333	0.4167	3.9167	0.1667	3.2500	3.5833	3.8333	3.8333	3.8333	1.5833	2.5000	3.2500	2.7500	1.6667	1.5833
DTB7	3.2500	0.4167	2.7500	0.2500	3.5833	2.0833	3.1667	2.8333	3.5000	1.7500	2.9167	3.1667	1.4167	0.5000	1.9167
DTB8	3.3333	0.7500	2.2500	0.3333	2.7500	1.6667	1.7500	3.7500	2.5833	2.2500	0.4167	3.2500	1.6667	0.5000	0.3333
DTB9	1.5000	0.2500	2.0833	1.0000	1.0833	0.1667	2.3333	0.3333	2.8333	3.3333	0.3333	1.0000	0.1667	2.0000	2.0833
DTB10	2.6667	4.0000	2.5833	0.2500	1.6667	3.4167	3.1667	2.9167	3.1667	3.5000	3.5833	2.6667	2.8333	1.0000	1.2500
DTB11	0.1667	1.9167	2.4167	2.5000	1.8333	1.7500	1.5833	1.3333	1.8333	3.1667	2.7500	2.0833	2.0000	0.2500	0.0833
DTB12	3.0000	2.0000	1.7500	0.1667	2.0833	0.1667	0.4167	0.2500	3.1667	1.9167	2.4167	3.4167	2.9167	1.8333	1.0833
DTB13	1.4167	0.7500	3.3333	1.0000	2.4167	1.8333	2.2500	2.8333	2.8333	1.5833	2.7500	1.6667	2.9167	1.2500	1.8333
DTB14	1.6667	1.6667	1.7500	1.0000	3.2500	3.5000	0.3333	2.0833	1.9167	2.0833	0.5833	3.5000	2.8333	2.5833	3.0833
DTB15	2.0000	2.0000	1.9167	1.3333	2.0000	3.3333	2.0000	2.0833	1.9167	1.8333	1.2500	3.5833	3.5000	2.0833	3.0833

Table A2 Normalized matrix

	DTB1	DTB2	DTB3	DTB4	DTB5	DTB6	DTB7	DTB8	DTB9	DTB10	DTB11	DTB12	DTB13	DTB14	DTB15
DTB1	0.0063	0.0050	0.0070	0.0037	0.0079	0.0046	0.0055	0.0057	0.0041	0.0046	0.0006	0.0052	0.0037	0.0002	0.0002
DTB2	0.0081	0.0081	0.0079	0.0031	0.0066	0.0072	0.0065	0.0070	0.0076	0.0013	0.0048	0.0081	0.0050	0.0041	0.0031
DTB3	0.0048	0.0011	0.0072	0.0061	0.0026	0.0009	0.0035	0.0074	0.0055	0.0048	0.0057	0.0079	0.0004	0.0002	0.0006
DTB4	0.0031	0.0007	0.0059	0.0039	0.0035	0.0022	0.0024	0.0024	0.0009	0.0037	0.0020	0.0048	0.0039	0.0015	0.0030
DTB5	0.0052	0.0013	0.0057	0.0017	0.0070	0.0033	0.0050	0.0065	0.0057	0.0041	0.0026	0.0039	0.0042	0.0037	0.0037
DTB6	0.0052	0.0009	0.0087	0.0004	0.0072	0.0079	0.0085	0.0085	0.0085	0.0035	0.0055	0.0072	0.0061	0.0037	0.0035
DTB7	0.0072	0.0009	0.0061	0.0006	0.0079	0.0046	0.0070	0.0063	0.0078	0.0039	0.0065	0.0070	0.0031	0.0011	0.0042
DTB8	0.0074	0.0017	0.0050	0.0007	0.0061	0.0037	0.0039	0.0083	0.0057	0.0050	0.0009	0.0072	0.0037	0.0011	0.0007
DTB9	0.0033	0.0006	0.0046	0.0022	0.0024	0.0004	0.0052	0.0007	0.0063	0.0074	0.0007	0.0022	0.0004	0.0044	0.0046
DTB10	0.0059	0.0089	0.0057	0.0006	0.0037	0.0076	0.0070	0.0065	0.0070	0.0078	0.0079	0.0059	0.0063	0.0022	0.0028
DTB11	0.0004	0.0042	0.0054	0.0055	0.0041	0.0039	0.0035	0.0030	0.0041	0.0070	0.0061	0.0046	0.0044	0.0006	0.0002
DTB12	0.0066	0.0044	0.0039	0.0004	0.0046	0.0004	0.0009	0.0006	0.0070	0.0042	0.0054	0.0076	0.0065	0.0041	0.0024
DTB13	0.0031	0.0017	0.0074	0.0022	0.0054	0.0041	0.0050	0.0063	0.0063	0.0035	0.0061	0.0037	0.0065	0.0028	0.0041
DTB14	0.0037	0.0037	0.0039	0.0022	0.0072	0.0078	0.0007	0.0046	0.0042	0.0046	0.0013	0.0078	0.0063	0.0057	0.0068
DTB15	0.0044	0.0044	0.0042	0.0030	0.0044	0.0074	0.0044	0.0046	0.0042	0.0041	0.0028	0.0079	0.0078	0.0046	0.0068

Data availability statement Data related to this research are available from the corresponding author on request.

Declarations

Competing interests The authors report no conflict of interest.

References

Benyam AA, Soma T, Fraser E (2021) Digital agricultural technologies for food loss and waste prevention and reduction: Global trends, adoption opportunities and barriers. Journal of Cleaner Production 323:129099. https://doi.org/10.1016/j.jclepro.2021.129099

Beriya A (2022) India digital ecosystem of agriculture and agristack: an initial assessment (No. 68). ICT India working paper. Available at: https://www.econstor.eu/handle/10419/250913. Accessed 16 April 2022

Burgos D, Ivanov D (2021) Food retail supply chain resilience and the COVID-19 pandemic: a digital twin-based impact analysis and improvement directions. Transport Res E-Log 152:102412. https://doi.org/10.1016/j.tre.2021.102412

Coelho F, Relvas S, Barbosa-Póvoa AP (2021) Simulation-based decision support tool for in-house logistics: the basis for a digital twin. Computers & Industrial Engineering 153:107094. https://doi.org/10.1016/j.cie.2020.107094

Cruz-Jesus F, Pinheiro A, Oliveira T (2019) Understanding CRM adoption stages: empirical analysis building on the TOE framework. Computers in Industry 109:1–13. https://doi.org/10.1016/j.compind.2019.03.007

Defraeye T, Shrivastava C, Berry T et al (2021) Digital twins are coming: will we need them in supply chains of fresh horticultural produce?. Trends Food Sci Technol 109:245–258.https://doi.org/10.1016/j.tifs.2021.01.025

Defraeye T, Tagliavini G, Wu W et al (2019) Digital twins probe into food cooling and biochemical quality changes for reducing losses in refrigerated supply chains. Resour Conserv Recycl 149:778–794. https://doi.org/10.1016/j.resconrec.2019.06.002

Dutta J, Kausley S, Deshpande P (2020) Food freshness monitor: a smart platform to estimate food quality and reduce wastage. Retrieved from: https://www.tcs.com/content/dam/tcs/pdf/research-innovation/reimagining-research/reimagining-research-food-freshness-monitor.pdf. Accessed 16 April 2022

FAO (2020) The state of food security and nutrition in the world 2020. Retrieved from: https://www.fao.org/3/ca9692en/ca9692en.pdf. Accessed 25 July 2022

Fuller A, Fan Z, Day C, Barlow C (2020) Digital twin: Enabling technologies, challenges and open research. IEEE access 8:108952–108971. https://doi.org/10.1109/ACCESS.2020.2998358

Ganguly KK (2022) Understanding the challenges of the adoption of blockchain technology in the logistics sector: the TOE framework. Tech Anal Strat Manag 36(3):457–471. https://doi.org/10.1080/09537325.2022.2036333

Gartner (2019) How digital twins simplify the IoT. Retrieved from: https://www.gartner.com/smarterwithgartner/how-digital-twins-simplify-the-iot. Accessed 7 June 2022

Glaessgen E, Stargel D (2012) The digital twin paradigm for future NASA and US Air Force vehicles. In: 53rd AIAA/ASME/ASCE/AHS/ASC structures, structural dynamics and materials conference 20th AIAA/ASME/AHS adaptive structures conference 14th AIAA, p 1818. https://doi.org/10.2514/6.2012-1818

Gangwar H, Date H, Ramaswamy R (2015) Understanding determinants of cloud computing adoption using an integrated TAM-TOE model. Journal of enterprise information management 28(1):107–130. https://doi.org/10.1108/JEIM-08-2013-0065

García Á, Bregon A, Martínez-Prieto MA (2022) Towards a connected digital twin learning ecosystem in manufacturing: enablers and challenges. Comput Ind Eng 171:108463. https://doi.org/10.1016/j.cie.2022.108463

Govindan K, Nasr AK, Saeed Heidary M, Nosrati-Abargooee S, Mina H (2023) Prioritizing adoption barriers of platforms based on blockchain technology from balanced scorecard perspectives in healthcare industry: a structural approach. Int J Prod Res 61(11):3512–3526. https://doi.org/10.1080/00207543.2021.2013560

Gustavsson J, Cederberg C, Sonesson U, Van Otterdijk R, Meybeck A (2011) Global food losses and food waste, pp 1–38. Rome: FAO. Retrieved from: https://www.madr.ro/docs/ind-alimentara/risipa_alimentara/presentation_food_waste.pdf. Accessed 20 June 2022

Hald KS, Coslugeanu P (2022) The preliminary supply chain lessons of the COVID-19 disruption—What is the role of digital technologies? Operations Management Research 15(1):282–297. https://doi.org/10.1007/s12063-021-00207-x

Henrichs E, Noack T, Pinzon Piedrahita AM, Salem MA, Stolz J, Krupitzer C (2022) Can a byte improve our bite? an analysis of digital twins in the food industry. Sensors 22(1):115. https://doi.org/10.3390/s22010115

Ivanov D, Dolgui A (2022) Stress testing supply chains and creating viable ecosystems. Operations Management Research 15(1):475–486. https://doi.org/10.1007/s12063-021-00194-z

Ivanova IA, Leydesdorff L (2014) Rotational symmetry and the transformation of innovation systems in a Triple Helix of university–industry–government relations. Technological Forecasting and Social Change 86:143–156. https://doi.org/10.1016/j.techfore.2013.08.022

Kamble SS, Gunasekaran A, Kumar V, Belhadi A, Foropon C (2021) A machine learning based approach for predicting blockchain adoption in supply Chain. Technological Forecasting and Social Change 163:120465. https://doi.org/10.1016/j.techfore.2020.120465

Kamble SS, Gunasekaran A, Parekh H, Mani V, Belhadi A, Sharma R (2022) Digital twin for sustainable manufacturing supply chains: Current trends, future perspectives, and an implementation framework. Technological Forecasting and Social Change 176:121448. https://doi.org/10.1016/j.techfore.2021.121448

Kaviani MA, Tavana M, Kumar A, Michnik J, Niknam R, de Campos EAR (2020) An integrated framework for evaluating the barriers to successful implementation of reverse logistics in the automotive industry. Journal of Cleaner Production 272:122714. https://doi.org/10.1016/j.jclepro.2020.122714

Kinkel S, Baumgartner M, Cherubini E (2022) Prerequisites for the adoption of AI technologies in manufacturing–Evidence from a worldwide sample of manufacturing companies. Technovation 110:102375. https://doi.org/10.1016/j.technovation.2021.102375

Kraus S, Durst S, Ferreira JJ, Veiga P, Kailer N, Weinmann A (2022) Digital transformation in business and management research: An overview of the current status quo. International Journal of Information Management 63:102466. https://doi.org/10.1016/j.ijinfomgt.2021.102466

Kumar M, Choubey VK, Raut RD, Jagtap S (2023) Enablers to achieve zero hunger through IoT and blockchain technology and transform the green food supply chain systems. Journal of Cleaner Production 405:136894. https://doi.org/10.1016/j.jclepro.2023.136894

Kumar M, Raut RD, Sharma M, Choubey VK, Paul SK (2022) Enablers for resilience and pandemic preparedness in food supply chain. Operations Management Research 15:1198–1223. https://doi.org/10.1007/s12063-022-00272-w

Lau A, Höyng M (2023) Digitalization? A matter of trust: a double-mediation model investigating employee trust in management regarding digitalization. Review of Managerial Science 17(6):2165–2183. https://doi.org/10.1007/s11846-022-00598-6

Lepore D, Dubbini S, Micozzi A, Spigarelli F (2022) Knowledge sharing opportunities for Industry 4.0 firms. J Knowl Econ 13(1):501–520. https://doi.org/10.1007/s13132-021-00750-9

Lioutas ED, Charatsari C, De Rosa M (2021) Digitalization of agriculture: a way to solve the food problem or a trolley dilemma? Technology in Society 67:101744. https://doi.org/10.1016/j.techsoc.2021.101744

Majumdar A, Agrawal R, Raut RD, Narkhede BE (2023) Two years of COVID-19 pandemic: understanding the role of knowledge-based supply chains towards resilience through bibliometric and network analyses. Oper Manag Res 16:1105–1121. https://doi.org/10.1007/s12063-022-00328-x

Majumdar A, Garg H, Jain R (2021) Managing the barriers of Industry 4.0 adoption and implementation in textile and clothing industry: interpretive structural model and triple helix framework. Comput Ind 125:103372. https://doi.org/10.1016/j.compind.2020.103372

Masood T, Egger J (2020) Adopting augmented reality in the age of industrial digitalisation. Computers in Industry 115:103112. https://doi.org/10.1016/j.compind.2019.07.002

Melesse TY, Bollo M, Di Pasquale V, Centro F, Riemma S (2022) Machine learning-based digital twin for monitoring fruit quality evolution. Procedia Computer Science 200:13–20. https://doi.org/10.1016/j.procs.2022.01.200

Michnik J (2013) Weighted Influence Non-linear Gauge System (WINGS)–An analysis method for the systems of interrelated components. European Journal of Operational Research 228(3):536–544. https://doi.org/10.1016/j.ejor.2013.02.007

Michnik J (2018) The WINGS method with multiple networks and its application to innovation projects selection. Int J Appl Manag Sci 10(2):105–126. https://doi.org/10.1504/IJAMS.2018.092077

Perno M, Hvam L, Haug A (2022) Implementation of digital twins in the process industry: A systematic literature review of enablers and barriers. Computers in Industry 134:103558. https://doi.org/10.1016/j.compind.2021.103558

Pylianidis C, Osinga S, Athanasiadis IN (2021) Introducing digital twins to agriculture. Computers and Electronics in Agriculture 184:105942. https://doi.org/10.1016/j.compag.2020.105942

Qi Q, Tao F, Zuo Y, Zhao D (2018) Digital twin service towards smart manufacturing. Procedia CIRP 72:237–242. https://doi.org/10.1016/j.procir.2018.03.103

Rasheed A, San O, Kvamsdal T (2020) Digital twin: Values, challenges and enablers from a modeling perspective. IEEE Access 8:21980–22012. https://doi.org/10.1109/ACCESS.2020.2970143

Ribeiro-Navarrete B, Saura JR, Simón-Moya V (2023) Setting the development of digitalization: state-of-the-art and potential for future research in cooperatives. Rev Manag Sci 1–30. https://doi.org/10.1007/s11846-023-00663-8

Rockström J, Edenhofer O, Gaertner J, DeClerck F (2020) Planet-proofing the global food system. Nature food 1(1):3–5. https://doi.org/10.1038/s43016-019-0010-4

Rogers EM (2003) Diffusion of innovations, 5th edn. Free Press, Simon and Schuster, New York

Semeraro C, Lezoche M, Panetto H, Dassisti M (2021) Digital twin paradigm: A systematic literature review. Computers in Industry 130:103469. https://doi.org/10.1016/j.compind.2021.103469

Singh S, Shehab E, Higgins N, Fowler K, Tomiyama T, Fowler C (2018) Challenges of digital twin in high value manufacturing. SAE Technical Papers, 2018, Technical Paper number 2018-01-1928. https://doi.org/10.4271/2018-01-1928

Shoji K, Schudel S, Shrivastava C, Onwude D, Defraeye T (2022) Optimizing the postharvest supply chain of imported fresh produce with physics-based digital twins. Journal of Food Engineering. 329:111077. https://doi.org/10.1016/j.jfoodeng.2022.111077

Shukla M, Shankar R (2022) An extended technology-organization-environment framework to investigate smart manufacturing system implementation in small and medium enterprises. Computers & Industrial Engineering 163:107865. https://doi.org/10.1016/j.cie.2021.107865

Tao F, Zhang H, Liu A, Nee AY (2018) Digital twin in industry: State-of-the-art. IEEE Transactions on Industrial Informatics 15(4):2405–2415. https://doi.org/10.1109/TII.2018.2873186

Tebaldi L, Vignali G, Bottani E (2021) Digital twin in the agri-food supply chain: a literature review. In: Advances in production management systems. Artificial intelligence for sustainable and resilient production systems: IFIP WG 5.7 international conference, APMS 2021, Nantes, France, September 5–9, 2021, proceedings, part IV (pp 276-283). Springer International Publishing. https://doi.org/10.1007/978-3-030-85910-7_29

Tornatzky LG, Fleischer M (1990) The processes of technological innovation. Lexington Books

Tozanli Ö, Saénz MJ (2022) Unlocking the Potential of Digital Twins in Supply Chains. MIT Sloan Management Review 63(4):1–4

Tzachor A, Richards CE, Jeen S (2022) Transforming agrifood production systems and supply chains with digital twins. npj Sci Food 6(1):47. https://doi.org/10.1038/s41538-022-00162-2

Vallejo ME, Larios VM, Magallanes VG et al (2021) Creating resilience for climate change in smart cities based on the local food supply chain. In: 2021 IEEE international smart cities conference, pp 1–7. https://doi.org/10.1109/ISC253183.2021.9562795

Verdouw C, Tekinerdogan B, Beulens A, Wolfert S (2021) Digital twins in smart farming. Agricultural Systems 189:103046. https://doi.org/10.1016/j.agsy.2020.103046

Verma S, Bhattacharyya SS (2017) Perceived strategic value-based adoption of Big Data Analytics in emerging economy: A qualitative approach for Indian firms. Journal of Enterprise Information Management 30(3):354–382. https://doi.org/10.1108/JEIM-10-2015-0099

Wang K, Xie W, Wang B, Pei J, Wu W, Baker M, Zhou Q (2020) Simulation-based digital twin development for blockchain enabled end-to-end industrial hemp supply chain risk management. In: 2020 winter simulation conference (WSC). IEEE, pp 3200–3211. https://doi.org/10.1109/WSC48552.2020.9384115

Wang W, Tian Z, Xi W, Tan YR, Deng Y (2021) The influencing factors of China's green building development: An analysis using RBF-WINGS method. Building and Environment 188:107425. https://doi.org/10.1016/j.buildenv.2020.107425

Werner R, Takacs R, Geier D, Becker T, Weißenberg N, Haße H, Sollacher R, Thalhofer M, Schumm B, Steinke I (2020) The challenge of implementing digital twins in operating value chains. In: Herwig C, Pörtner R, Möller J (eds) Digital twins, vol 177. Adv Biochem Eng Biotechnol. Springer, Cham, pp 127–166. https://doi.org/10.1007/10_2020_153

West TD, Blackburn M (2017) Is digital thread/digital twin affordable?. A systemic assessment of the cost of DoD's latest manhattan project. Procedia Comput Sci 114:47–56. https://doi.org/10.1016/j.procs.2017.09.003

Yadav VS, Majumdar A (2023) Mitigating the barriers of industrial symbiosis for waste management: an integrated decision-making framework for the textile and clothing industry. Waste Manag Res 1–12. https://doi.org/10.1177/0734242X231197367

Yadav VS, Singh AR, Gunasekaran A, Raut RD, Narkhede BE (2022) A systematic literature review of the agro-food supply chain: Challenges, network design, and performance measurement perspectives. Sustainable Production and Consumption 29:685–704. https://doi.org/10.1016/j.spc.2021.11.019